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Sustainability of the Theories Developed by Mathematical Finance and Mathematical Economics with Applications

Edited by
Wing-Keung Wong

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Special Issue Editor

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About the Special Issue Editor

Wing-Keung Wong obtained his Ph.D. from the University of Wisconsin-Madison, the USA with a major in Business Statistics (Statistics and Finance) and obtained his Bachelor degree from the Chinese University of Hong Kong, Hong Kong, with a major in Mathematics and a double minor in Economics and Statistics. Currently, he is a Chair Professor at the Department of Finance, Asia University. He was a Full Professor at the Department of Economics, Hong Kong Baptist University, and Deputy Director at Risk Management Institute, National University of Singapore. Professor WONG appears in "Who's Who in the World" and gets Albert Nelson Marquis Lifetime Achievement Award. 2017, Marquis Who's Who. His Erdos number is 3. He is ranked top 1% by Social Science Research Network and in the list of top Taiwan economists and Asian economists and top economists by RePEc. He has published more than three hundred papers including papers published in some top journals. He has more than 8400 citations in Google Scholar, more than 6100 citations in Researchgate, and more than 2400 citations in Mendeley. His h-index is 52, (36 since 2015) and i10-index is 177, (146 since 2015) by Google Scholar citation. He has been serving international academies, government, society, and universities, providing consultancy to several Government departments and corporations, and giving lectures and seminars to several universities. For example, he has been serving as editor, guest leading editor, advisor, associate editor for some international journals, appointed as an advisor/member of various international associations/institutes, serving as a referee for many journals/conferences, supervising solely or jointly several overseas graduate students, appointed as an external reviewer and external examiner by other universities, and invited by many universities/institutions to present papers or conduct seminars. He has published more than three hundred papers including many top journal publications.

Preface to "Sustainability of the Theories Developed by Mathematical Finance and Mathematical Economics with Applications"

Mathematical Finance and Mathematical Economics play a vital role in many fields in the sustainability of Economics and Finance. In particular, they provide the theories and tools that have been widely used in all areas of economics and finance. Knowledge of mathematics, probability, and statistics is essential for the development of economic and financial theories, and for testing their validity through the analysis of empirical real-world data. For example, mathematics, probability, and statistics could help to build sustainable monetary and fiscal policies, and to develop pricing models for financial assets, such as equities, bonds, currencies, and derivative securities.

A Special Issue of *Sustainability*, focusing on the theories developed in *Mathematical Finance and Mathematical Economics with Applications*, edited by Wing Keung Wong, will be devoted to advancements in theory development, with applications for Mathematical Finance and Mathematical Economics. This Special Issue will bring together the theory, practice, and applications of Mathematical Finance and Mathematical Economics. The sustainability of the theories developed in *Mathematical Finance and Mathematical Economics with Applications* in the areas of economics and finance will also be analyzed. This Special Issue will also bring together practical, state-of-the-art applications of mathematics, probability, and statistical techniques in economics and finance, and consider their sustainability.

We invite scholars to contribute original research articles that advance the use of mathematics, probability, and statistics in the areas of economics and finance and their sustainability. All submissions must contain original unpublished work not being considered for publication elsewhere.

The Efficient Market Hypothesis believes that it is impossible for an investor to outperform the market, because all available information is already built into stock prices. However, some anomalies could persist in stock markets, while some other anomalies could appear, disappear, and re-appear again without any warning. To explore new theories with applications in this direction, the Special Issue on *Efficiency and Anomalies in Stock Markets*, edited by Wing-Keung Wong, is devoted to advancements in the theory development on market efficiency and anomalies in stock markets, as well as applications in market efficiency and financial anomalies in 2019. We invite investigators to submit manuscripts of original innovative research in theory, practice, and applications in the areas of market efficiency and anomalies in stock markets, to be considered for publication in *Sustainability*. We are open to interesting and imaginative ideas that fit within the spirit and scope of the call for papers—and these should have a quantitative orientation. The Special Issue of *Mathematical Finance and Mathematical Economics with Applications* has published 18 papers.

Wing-Keung Wong
Special Issue Editor

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Article

Does Herding Bias Drive the Firm Value? Evidence from the Chinese Equity Market

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Abstract: Equity markets play a pivotal role in the sustainability of developing countries, such as China. The literature on the detection of herding biases is confined to the aggregate level (firms, sector/industry and market). The present study adds to the behavioral finance literature by addressing the surprisingly unnoticed phenomena of the behavioral impact of herding bias on firm value (FV) at the firm level, using the sample of A-Shares listed firms at the Shanghai and Shenzhen Stock Exchanges (SSE and SZSE) under panel fixed effect specification. Initially, we detect the existence of investors and managers herding (IHR and MHR) biases at firm-level, and later, we examine their impact (distinct and interactive) upon the FV. The empirical results document the presence of IHR and MHR bias at market, sector and firm-level in both equity markets, which potentially drive the FV, while the impact is more pronounced during the extreme trading period. The findings are robust under different time intervals, and industry classification, therefore, offers useful policy implications to understand the behavioral dynamics of investors and managers.

Keywords: Investor herding bias; manager herding bias; firm value; Shanghai stock exchange; Shenzhen stock exchange

1. Introduction

The stock market trading dilemma is the cumulative reflections of investors' behavior [1]. Investors exhibit behavioral irregularities (biases) which potentially influence market efficiency [2,3]. Among these biases, herding bias is the most prominent, which is associated with the trading behavior of financial markets' participants [4,5]. It has become a subject of widespread interest in the recent decade [6–8]. Herding refers to the situation wherein rational people start behaving irrationally by imitating the judgments of others while making decisions [3]. Herding theories posit that market participants prefer to follow the financial experts in their trading patterns instead of their own source of information [9].The study of [10] believes that the herding of investors is one of the major risk factors that is typically ignored by statistical approaches.

In the past decade, the study of herding documents this diverse behavioral pattern across the globe. In the context of the U.S. markets, Christie and Huang [5] report the absence of herding bias, even during extreme market movements. Conversely, Choi and Sias [11] point out the presence of a strong institutional industry herding bias. Likewise, Wang and Zhang [12] investigate the impact of individual investor trading on the firm value (FV) at the New York Stock Exchange (NYSE), and find the positive impact of investor trading on FV. European evidence [13] illustrates the presence of herding bias in the "during crises" period. Also, Walter and Moritz Weber [14] identify the herding bias of mutual fund managers in Germany during extreme market movements. Chinese, Taiwanese and South Korean stock markets also reveal herding behavior [15–18]. In the Chinese equity market, Demirer and Kutan [19] empirically analyze the behavior of return dispersions during periods of unusually large upward and downward changes in the market index of both the SSE and SZSE, and conclude that the Chinese Market is free from herding bias, and a similar approach is used by Demirer et al. [20]. Conversely, Tan et al. [21] explore the evidence of herding bias at the SSE and the SZSE, the A-share and B-share markets. They also report the existence of herding bias in both rising and falling market conditions, specifically more pronounced in the A-shares of the Shanghai Market during rising market conditions. Bo et al. [22] witness the investment herding bias among the corporate board, directors, and CEOs of non-financial firms from 1999 to 2004, and the consequent positive and significant impact on the FV. Similarly, another group of studies [23–25] report the mixed results of herding bias at the SSE and SZSE.

The above-mentioned studies highlight herding bias in two ways: First, the evidence of investors herding at market, industry/sector and firm-level during the extreme market conditions [17,19]; Second, the evidence of an investment-herding bias of the corporate manager [14] and their impact on the FV [22]. For the best of our knowledge, there is not a single study which explains the individual and interactive impact of investor and manager herding (IHR and MHR) biases on the FV. So, motivated by the recent studies [6,12,22] that manager and investor demonstrate herding bias in their investment decision, this study empirically investigates the following questions:

1. Whether the investor herding bias exists at market-, sectors- and firm-level Chinese equity markets?
2. Do managers of the firm also exhibit herding bias in Chinese equity markets?
3. What is the individual and interactive impact of investors' and managers' herding bias on the FV?

The Chinese Financial Equity Market is important to be analyzed as it has an influence on integrated markets [26], while in China there is a need to strengthen the financial resources for sustainable development and poverty reduction [27]. Based on the literature and the questions stated above, this study adds to the existing literature in the following ways: Firstly, it hypothesizes the presence of herding bias in the Chinese equity markets at the market and industry/sector level, in line with [8,15,19,28], and later it extends the phenomena at the firm level, which is a unique addition to the behavioral finance literature. Importantly, the market and sector level herding is insufficient to explain the investor's behavior associated to the firm, as Demirer and Zhang [17] find that the firm characteristics, their size and the past return has a significant effect on the herding behavior of the investor. Secondly, to the best of our knowledge, this is the first study that examines the impact of IHR and MHR on the FV. Finally, another most interesting contribution is in the form of the interactive impact of both IHR and MHR on the FV, which provides insights into understanding how both stakeholders jointly influence the FV.

Overall results demonstrate that: (i) Herding behavior exists at market-, sector- and firm-level at the SSE and SZSE, and a non-linear and significant relationship exists between stock return and cross-sectional absolute deviation (CSAD), which seems to be more pronounced in herding bias at all levels at the SZSE. The CSAD model explains 95% and 99% herding bias at the market level, 26% and 32% at sectors level, and 10% and 12% at the firm level at SSE and SZSE, respectively. While an absolute investment deviation model detects 51% and 54% of managers herding bias at SSE and SZSE, respectively.

The empirical results also suggest that IHR and MHR affect the FV significantly during the extreme trading period (2014 to 2015), at both stock exchanges, while the interaction of IHR and MHR reveals the same at the SZSE in 2013. Importantly, the results are robust under different time intervals and industry classification.

The rest of this study is arranged as follows: Section 2 describes a brief literature and hypotheses development. Section 3 explains the methodological approach, including variable definitions, data sources and the sample period. Section 4 states the empirical results and discussion, while the final section concludes the study along with policy recommendations.

2. Literature Review and Hypothesis Development

Prior literature finds a diverse herding bias among participants in various stock markets. Empirical evidence on U.S. and Europeans investors and managers exhibits the presence of herding bias among mutual fund managers [29], analysts recommendation [30] and pension fund managers [31]. The aggregate effect of herding behavior is more prevalent in international markets, especially in emerging markets. Chang et al. [15] find significant evidence of herding bias in Taiwan and South Korea, alimited bias in Japan, and no bias in the U.S. and Hong Kong.

Later on, the Bueno [32] document herding bias in both theA-shares and B-shares of theChinese Stock Market. Furthermore, empirical analysis of herding on eighteen international markets by Chiang and Zheng [33] show the existence of herding in seven Asian and six advanced markets, whereas thenonexistence of herding behavior among both Latin American and U.S. markets, except during a crises period. Recent studies of Balcilar et al. [34] and Zheng et al. [35] also document herding behavior in the Gulf Arab and Asian markets. In Pakistan, the study of Javed et al. [36] and Javaira and Hassan [37] found no evidence of herding behavior in KSE 100 index companies at the Karachi Stock Exchange (KSE) for the period of 2002 to 2014. Whereas, the study of Yousaf et al. [38] on investor herding behavior in the Pakistan Stock Market during 2004 to 2014 reports the existence of herding behavior in the market, particularly in 2005 to 2008. Likewise, the empirical work of Shah et al. [28] for 2004 to 2013 also supports the significant evidence of herding behavior in this Pakistan Stock Market, specifically during the extreme market movements. Additionally, they found more than 50% of sectors at the PSX exhibit herding behavior during the upward market movements.

Demirer and Kutan [19] examine the presence of herd formation in Chinese markets using both individual firm and sector level data. They analyze the behavior of return dispersions during periods of unusually large upward and downward changes in the market index. They also distinguish sample data between the Shanghai and Shenzhen stock exchanges at the sector-level. Their findings show that herding bias does not exist in Chinese markets. However, comparing return dispersions for upside and downside movements of the market, these return dispersions during extreme downside movements of the market are much lower than those for upside movements, indicating that stock returns behave more similarly during down markets. Munkh-Ulzii et al. [39] find the presence of significant herding behavior in Chinese and Taiwan stock markets. Tan et al. [21] explore herding behavior in dual-listed Chinese A-share and B-share stocks. They find evidence of herding within both the Shanghai and Shenzhen A-share markets that are dominated by domestic individual investors, and also within both B-share markets, in which foreign institutional investors are the main participants.

Herding occurs in both rising and falling market conditions. Herding behavior by A-share investors in the Shanghai Market is more pronounced under conditions of rising markets, high trading volumeand high volatility, while no asymmetry is apparent in the B-share market. Lee et al. [24] document the effect of institutional herding on future stock returns in the China A-share Market at both the market and industry level from 2003 to 2012. Using a unique institutional holding database, they test the herding effect at different time horizons. The results suggest that institutional herding has a significantly positive effect on future excess returns for A shares in the short, medium and long periods of time. In the China A-share market, institutional herding is more significant on the buy-side than the sell-side due to short sell restrictions.

At the industry level, manufacturing and construction sectors experience an institutional herding effect at all time horizons. The financial industry is found to present a significant institutional effect only in the long term.

The institutional herding has a positive and significant impact on the medium-term and long-term excess stock returns in the rest of ten sectors. Yao et al. [25] report the existence and prevalence of investor herding behavior in a segmented market setting, the Chinese A and B stock markets. The results indicate that investors exhibit different levels of herding behavior, in particular, herding strongly exists in the B-share markets. They also find that across markets, herding behavior is more prevalent at industry-level, is stronger for the largest and smallest stocks, and is stronger for growth stocks relative to value stocks. Herding behavior is also more pronounced under conditions of declining markets. Over the sample period which we are examining, herding behavior diminishes over time. The results provide some indication to the effectiveness of regulatory reforms in China aimed at improving information efficiency and market integration.

Lao and Singh [23] investigated herding behavior in the Chinese and Indian stock markets. Their results support that although both the Indian and Chinese stock markets are considered inefficient with low information disclosure standards, the Chinese Market exhibits herding behavior greater than the herding behavior in the Indian Market. Nevertheless, in both markets, herding behavior finds itself stronger in large market movements. Asymmetry investigation discovered that the Chinese Stock Market has the most profound herding behavior when the market is low and trading volume is high. Instead, in the Indian Market, herding behavior is observed when the market is high. In the Indian Market, herding behavior also had no association with trading volume. The reasons for herd behavior existing in the Chinese Stock Market, in both up and down states, are analyst forecast, short-term investor horizon, and inclusion of risk in decision making [40].

Although herding mentioned in the above studies contributesmuch to a better understanding of investor behavior at the SSE and SZSE, their aggregate results are confined at market and sector level, which also explains the mixed results, existence and nonexistence, of herding bias over time. Thus, consistent with the prior literature, we postulate the first hypothesis to test whether herding bias exists at the SSE and the SZSE during the sample period 2008 to 2017.

Hypothes (H1). *Stock prices show significant herding behavior at the market and sector level.*

Investors usually invest in those stocks with which they are familiar. Study of Huberman [41] considers the leading example of this phenomena. He explores the higher attention of employees in buying the security of those firms for which they work or are informed about from their peers. Ha [42] examined the impact of herding on the stock performance, and documentsthe very strong impact of herding on the stock returns and stock returns affect book to the market value of firms [43]. Also, Van Nieuwerburgh and Veldkamp [44] found the investors trending in home stock are much higher than the foreign stocks, while careful policy actions are needed to prevent malpractices [45]. Gebka and Wohar [46] document stronger irrationality behavior among the investors particularly in the Consumer Services, Oil and Gas and Basic Materials industries in the international equity markets. Following these examples, it can be figured that investors mostly invest in familiar stocks and industries preferably in the national stock market. Focusing on individual stock information for a specific industry may help to explore the herd behavior better rather than at the aggregate industry or market level. To address the answer to this question, we postulate the second hypothesis as below:

Hypothes (H2). *Stock prices show significant herding behavior at the firm level in the Chinese stock market.*

Detection of herding at any level is not enough to explain the behavior of investors toward the specific firm. Investors usually consider the FV while making their investment decision. The market value of stock reacts on the price momentum based upon the frequency of the investors' trade. Therefore, investors' trading patterns show many behavior irregularities and biases which affect the firm's performance. Among these biases, herding bias is the main behavioral bias [4], which significantly affects the firm's performance [6,8,22]. Wang and Zhang [12] elaborate on the positive impact of investor trading on the FV.

Also, Hilliard and Zhang [47] find the weaker size and price to book value effect on the herding behavior of the Chinese Stock Market relative to U.S. markets over the period of 1999 to 2012. Our study differs uniquely from the prior studies, and tries to capture the impact of the herding bias of investors, at the individual firm, on the FV listed as A-share at the SSE and SZSE. To examine such a relationship, we construct the following hypothesis.

Hypothes (H3). *Ceteris paribus, IHR bias has a positive impact on the FV.H3: Ceteris paribus, IHR bias has a positive impact on the FV.*

Effects of herding are not bounded to the investors only. Firms' managers also exhibit herding behavior in their financial decisions. Theories on herding behavior in standard literature assume that the information set upon which corporate managers are making investment decisions is truly perfect, and informative under a mature market system that guarantees a transparent corporate reporting system, mature laws and regulations, strong shareholders' protection and effective corporate governance mechanisms. Under such circumstances, the manager should make investment decisions based on the information set relevant to the firm. In contrast, Prendergast and Stole [48] discuss the herding intention of the managers who make investment decisions over time.Demirer and Zhang [17] find that small firms with a high level of herding significantly underperform from those small firms that experience low herding. They observe no significant interactions between book-to-market and market beta with herding. Chen and Demirer [8] point those industries that experience a high level of herding yield higher subsequent returns, regardless of their past performance.

Theories on herding find firms' managers usually follow their peers in investment decisions, instead of relying on their own source of information [9]. Garber [4] elaborates herding behavior as the most prominent bias in the psychology of judgment. In the recent past, the studies on manager investment herding behavior present the diverse behavioral pattern across the world. Fong et al. [49] demonstrate four general theories, classified into twoparts: Thefirst part belongs to intentional herding, and the second for unintentional herding. The authors state why managers may engage in herding behavior in their investment decisions as such: (1) Firm managers are subject to reputational risk when they behave differently from the crowd. Thus they may ignore private information to trade with the herd. (2) Managers may infer the private information of rival managers (perceived on their prior trades), resulting in the formation of informational cascades. (3) Managers may also receive similar private information because they also examine the same priced factors which caused them to arrive at similar conclusions regarding individual stocks. (4) Managers may exhibit similar aversions to stocks showing characteristics, such as low liquidity or low analyst coverage.

In the U.S. and European markets, herding behavior among managers of different industries is different. Choi and Sias [11] document strong institutional herding in U.S. corporations. Also, Walter and Moritz Weber [14] pinpoint the herding behavior of mutual fund managers in Germany. TheSouth Korea, Taiwanand China markets also exhibit herding behavior [15,16]. Many scholars examine the relationship between managerial career concerns and herding. Devenow and Welch [50] analytically illustrate herd behavior in making corporate investment decisions. In light of the above literature, we postulate hypothesis 4:

Hypothes (H4). *MHR bias has a positive impact on FV.*

Firm financial performance is considered the most important indicator for investors and managers for the evaluation of their financial decisions. It has broad implications for investments, capital allocation and market efficiency of the business. Alabass [6] and Bo et al. [22] demonstrate a positive and significant impact of MHR bias on the FV. Theprevious two hypotheses, H3 and H4, are constructed to test the

IHR and MHR bias individually. Perhaps it might be more logical to test the combined effect of herding bias to explore the magnitude of firm financial performance during the trading period. To investigate the combined effect of IHR and MHR bias on the FV, we test the following hypothesis:

Hypothes (H5). *Interaction of the IHR and MHR has a positive influence on FV.*

3. Methodological Approach

3.1. Data Source and Study Period

In this study, data are compiled from two data series of China Stock Market & Accounting Research (CSMAR). Firstly, we collect stock-based data, e.g., closing price, trading volume for individual stocks, sector/industry indices and market indices from stock market series during the sample period of 2008 through 2017. Secondly, we collect firm-level data, e.g., market to book value (MB), cash flow (CF), firm leverage (FL), firm growth (FG) and firm size (FS) from the annual audited financial statement. Initially, we consider all the firms listed with Shanghai and Shenzhen Stock Exchanges (SSE and SZSE) during the stated period. Later the data constraint problem limits our sample to 664 and 379 from 41 and 67 sectors at the SSE and SZSE, respectively.

These sub-sections initially describe the detection mechanisms of investors herding (IHR) and managers herding (MHR) biases market, sector and firm-level, and later explain the fixed effect specification used to examine the impact of IHR and MHR on firm value (FV).

3.2. Investors Herding

Since there is no direct measure of herding in financial markets, in financial literature different proxies are used to capture it indirectly at different time spans. Accordingly, the herding behavior can be summarized in two ways. [17] first employs the asymmetric trading orders of buying and selling the security in the market, which shows herding behavior on the buying side or the selling side, e.g., if the buyer orders are more than the selling order, then it is identified as herd in buying, otherwise herd in selling. This strand of the literature explains herding behavior at the investors level [31]. Whereas, the later detects the herding behavior using a regression approach based on an asset-pricing model which links the cross-sectional deviation of security returns to the extreme movements of industry returns and market return. Usually, this approach captures herding behavior at the market/industry level. Mostly, the herding literature falls into the second approach (market and sector level), because in this way an appropriate sample of market participants can be analyzed at different time spans. This approach follows two common methodologies for herding bias. First is CSSD, and the second is Cross Sectional Absolute Deviation (CSAD). CSSD, initially proposed by Christie and Huang [5], calculates the cross-sectional deviation of stock returns as:

$$\mathrm{CSSD_t} = \sqrt{\frac{\sum_{i=1}^{n}(r_{i,t} - r_{m,t})^2}{n_t - 1}} \tag{1}$$

Where n denotes the number of listed firms in the portfolio, $r_{i,t}$ is security i return at time t, and $r_{m,t}$ explains the equally-weighted returns of the portfolio at deviations. Christie and Huang [5] suggest that herding exists if the stock return dispersion by CSSD is significantly lower. Later on, Chang et al. [15] generalize the method for the herding behavior by adding the phenomena of CSAD, which is built on CAPM, for all market conditions. Our study is also based on the CSAD approach [15] for the detection of herd bias among the market participants, which is calculated as:

$$\mathrm{CSAD_t} = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{2}$$

Chang et al. [15] suggest that there should be a linear correlation of CSAD with the absolute value of the security. However, when herd bias occurs, investor trades follow the same market direction, and individual security returns tend to cluster around the overall market return. Thus, the linear relation turns to a nonlinear one.

Under the following situation, the negative and significant nonlinear relationship between CSAD and stock market return illustrates the presence of herding. Hence, the CSAD model for exploring herding behavior is constructed as follows:

$$CSAD_{m,t} = \alpha_0 + \gamma_1 \left|R_{m,t}\right| + \gamma_2 R^2_{m,t} + \varepsilon_t \tag{3}$$

Where negative and significant $\gamma 2$ shows the presence of herding bias. As our study also focuses on industry level and firm-level herding, we transform the above model, as below:

$$CSAD_{Ind,t} = \frac{1}{N} \sum_{i=1}^{N} \left|R_{i,t} - R_{ind,t}\right| \tag{4}$$

$$CSAD_{ind,t} = \alpha_0 + \gamma_1 \left|R_{ind\_m,t}\right| + \gamma_2 R^2_{ind\_m,t} + \varepsilon_t \tag{5}$$

In Equation (4), the $CSAD_{ind,t}$ is calculated based on N, the wholenumber of firms' security returns within the industry. For the calculation of $CSAD_{ind,t}$, we use the average industry return ($R_{ind,t}$) for each of theindustry in the markets, along with the individual stock return ($R_{i,t}$) listed in the same industry.

In Equation (5), $R_{ind\_m,t}$ = $R_{ind,t}$ - $E(R_{ind,t})$, where $E(R_{ind,t})$ is the expected industry return which is based on CAPM, and calculated as $E(R_{ind,t}) = \alpha + \beta R_{m,t}$.

$$CSAD_{firm,t} = \frac{1}{n} \sum_{i}^{n} \left|R_{i,t} - R_{ind,t}\right| \tag{6}$$

$$CSAD_{firm,t} = \alpha_0 + \gamma_1 \left|R_{firm\_ind,t}\right| + \gamma_2 R^2_{firm\_ind} + \varepsilon_t \tag{7}$$

In Equation (6), we extend the model and calculate $CSAD_{firm\_ind,t}$ of all firms' security returns within the sectors, based on n numbers of observations. Moreover, in Equation (7), we replace return of firm in the industry at time t instead of the return of industry at time t in the Equation (5), where $R_{firm\_ind,t}$ = $R_{firm\_ind,t}$ - $E(R_{firm\_ind,t})$, as expected firm return in the sector based on $E(R_{firm\_ind,t})$= $\alpha + \beta_{Rind,t}$. We calculate stock returns of market, industry and firm as R =log(P_t/ P_{t-1}), where Pt denotes the recent price of stock and P_{t-1} is the last price of the stock. For consideration of handling the outliers, we trim the return data at the 99^{th} percentile. The specification of this model is consistent with [25]. On the basis of $\gamma 2$ of the ($CSAD_{firm\_ind,t}$) model, we construct our index investor herding bias (IHR) of each firm from each sector and assign dummy values 1, if $\gamma 2$ of ($CSAD_{firm\_ind,t}$) model is negative and significant and 0 otherwise.

3.3. Managers Herding

We use an absolute investment deviation ratio model as a proxy of MHR bias as suggested by Alabass [6] andBo et al. [22]. In the investment ratio model, herding exists if managers of firm i follow the investment decisions of their peers. In normal practice, it is impossible to consider that managers observe the contemporaneous investment decisions of other firms while making their own investment decisions. Perhapsit is more logical to presume that firms' managers are aware of the average investment value of other firms, listed in the same industry, in recent years. Managers often consider the last year industry average investment value as a reference for their investment decisions, therefore, the proxy for investment herding is defined as:

$$MHR_t = \left\| \frac{I}{K_{i,t}} \right| - \left| \overline{\frac{I}{K_{-i,t-1}}} \right\| \tag{8}$$

Which is the absolute deviation of the investment ratios; the ratio of investment to the capital stock of firm *i* at the time *t*, and the average investment ratio of other firms in the same sectors, excluding firm *i* at time year (t-1). While computing the investment ratio $(I/K)_{i,t}$, we first sort the data by sectors, followed by sorting within sectors for the measurement of the average investment ratio $(\overline{I/K})_{-i,t-1}$ of other firms in the same sectors. Following Bo et al. [22] we also calculate net investment I, such as the net changes in fixed assets (FA) of the firm i.e., (I=ΔFA) and capital stock at the beginning of the period, $K_{i,t}$ by the total assets (TA) of a firm. A smaller investment deviation suggests herding, the managers of firm *i* make a similar investment decision to the other firms listed in the same industry. Therefore, based on a smaller investment deviation of the model as a proxy of manager herding, we construct a new index for MHR, and assign adummy value of 1 if herding exists, otherwise 0.

3.4. Herding and Firm Value

To examine the effect of IHR, MHR on FV, the theoretical association between these variables can functionally be expressed as:

$$FV_t = f(IHR_t,\ MHR_t,\ CF_t, FL_t,\ FS_t, FG_t) \tag{9}$$

We transformed Equation (1) into mathematical expression:

$$FV_t = \beta_0 + \beta_1 IHR_t + \beta_2 MHR_t + \beta_3 CF_t + \beta_4 FL_t + \beta_5 FS_t + \beta_6 FG_t + \gamma + \mu + \epsilon \tag{10}$$

In the above Equation, FV_t denotes FV as the dependent variable, and is measured by the market to book value (MB) [22,51–53]. IHR_t and MHR_t show investors and managers herding as independent variables, and this is measured by the methodologies of Chang et al. [15], and Bo et al. [22]. Whereas, CF_t for cash flow to assets, FL_t for firm leverage,FS_t for firm size and FG_t are control variables as suggested by bothChen and Lin [54] and Bo et al. [22]. γ and μ are used for industry and years fixed effects, whereas ϵ explains the error terms of the model. Table 1 presents the detailed information of all variables.

Table 1. Explanation of Variables.

Variable Type	Name	Proxy	Explanation
Dependent variable	FV_t	MB	Market value of assets/book value of assets
Independent variable	Investor herding (IHR)	Cross-sectional absolute deviation	Market, sector and firm-level bias exists if γ2 of CSAD has a significantly negative value. Dummy 1 is assigned when bias exists, otherwise it is 0
	Manager herding (MHR)	Investment to capital ratio	Bias exists if an absolute deviation of investment ratio would be minimum. Dummy 1 is assigned when bias exists, otherwise 0
Control variable	Cash flow to assets (CF)t	Cash flow at time t	Cash flow to assets ratio
	Firm leverage (FL)t	Firm leverage at time t	Total debt to equity ratio
	Firm size (FS)t	Firm size at time t	Natural log of total assets
	Firm growth (FG)t	Firm growth at time t	Natural log of sales

Source: Authors' own research, 2019.

4. Empirical Results and Discussion

Table 2 presents the descriptive analysis of the firm's financial data at the SSE and SZSE for the period of 2008 to 2017, in terms of mean, minimum and maximum values, and standard deviation of the FV, Tobin's Q—Ahmad et al. [55] and control variables such as cash flow (CF), firm leverage (FL), firm size (FS), and firm growth (FG). Column (1) and (6) report the mean values of FV, i.e., 1.88 and 2.136 with the standard deviation of 1.92 and 1.94, and the minimum to maximum range, 0.188 to 11.967 and 0 to 0.49, at the SSE and SZSE, respectively. While the rest of the columns explain the description of the control variables, where FS has a relatively higher mean value with lower deviation, and CF has a relatively least average value with least deviation among the firms of two stock exchanges.

Table 2. Descriptive Statistics at the Shanghai and Shenzhen Stock Exchanges (SSE and SZSE) (2008–2017).

Variable	SSE					SZSE				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	FV	CF	FL	FS	FG	FV	CF	FL	FS	FG
Mean	1.88	0.099	1.586	22.28	0.971	2.136	0.1	1.319	21.94	0.841
Std.Dev.	1.926	0.099	1.776	1.365	0.645	1.949	0.1	1.492	1.269	0.594
Min	0.188	0	−1.953	19.22	0.246	0.188	0	−1.953	19.22	0.246
Max	11.967	0.49	10.845	25.88	2.203	11.967	0.49	10.85	25.88	2.203
Obs	6640	6640	6640	6640	6640	3790	3790	3790	3790	3790

Source: Authors' own research, 2019.

The pairwise correlation results of Table 3 haveno evidence of multicollinearityamong variables of SSE and SZSE for the period of 2008 to 2017. All variables are significantly related to each other, except the CF in SZSE, which has a positive and insignificant relation with FG.

Table 3. Correlation matrix at SSE and SZSE (2008–2017).

Variables SSE/SZE	FV	CF	FL	FS	FG
FV	1	0.131 *	−0.162 *	−0.490 *	−0.335 *
CF	0.050 *	1	−0.138 *	−0.033 *	0.004
FL	−0.130 *	−0.128 *	1	0.191 *	0.159 *
FS	−0.528 *	−0.025 *	0.145 *	1	0.678 *
FG	−0.392 *	0.043 *	0.138 *	0.707 *	1

Note: * shows significance at the 0.05 level. The lower part of principal diagonal "1" explains correlation matrix for SSE and upper part present matrix for SZSE.Source: Authors' own research, 2019.

4.1. Herding at Equity Markets

This section presents the empirical results of herding bias at a market level between two stock markets, i.e., the SSE and the SZSE by using the CSAD model [15,28]. Therefore, a negative and significant γ_2 (CSAD model coefficient) exhibits evidence of herding behavior.

Table 4 exhibits the evidence of herding behavior by CSAD model in A-shares of SSE and SZSE during the sample period starting from 2008 to 2017. In Table 4, negative and significant γ_2 with coefficients (−1.146) and (−1.741), and t-values (−2.08) and (−4.49), present the evidence of a herding bias in the SSE and SZSE, respectively, during the said sample period. Furthermore, this herding bias is seeming more prevalent in the A- Shares of SZSE, at a 99% level of confidence, which are consistent with the literature [16,19].

Table 4. Level A-Share Herding Bias at SSE and SZSE (2008–2017).

$CSAD_{m,t}$	A	γ_1	γ_2	Adjusted R^2
SSE	0.013 ***	0.197 ***	−1.146 **	0.037
	(24.3)	(4.94)	(−2.08)	
SZSE	0.013 ***	0.209 ***	−1.741 ***	0.067
	(27.74)	(7.27)	(−4.49)	

Source: Authors' own research, 2019; Note: *,**,*** denote test statistics significant at 10%, 5%, and1% respectively, while t-value in parenthesis.

4.2. IHR Bias at Industry/Sector Level

Tables 5 and 6 incorporate the evidence of industry/sector level herding bias by CSAD model (5) in the A-shares of the SSE and SZSE. The results in Table 5 indicate herding bias among 11 sectors out of 41—these sectors are agriculture, food manufacturing, leather, fur, feathers and footwear production, petroleum processing, coking and nuclear fuel processing, metal products industry, housing construction, warehousing industry, other financial industry, health and comprehensive industry(γ_2 is negative and significant). Table 6 attributes investors' herding bias among 22 sectors out of 67 at the SZSE. These sectors include animal husbandry, forestry and fishery services, the agricultural and food processing industries, food manufacturing, the wood processing industry, culture and entertainment products manufacturing, the rubber and plastic products industry, non-ferrous metal smelting and rolling processing industry, instrumentation manufacturing, handling and transportation agency, internet and related services, ecological protection and environmental management, news and publishing, comprehensive, the wholesale industry, retail industry, air transport industry, catering, monetary financial services, the real estate industry, and media operations. While, 30/41 and 45/67 sectors at SSE and SZSE, respectively, are free from the herding, γ_2 ($CSAD_{int,t}$ model, coefficient) is negative/positive and insignificant. Our findings are supported by prior literature [16,19,28].

Table 5. Industry Herding Bias at the SSE (2008–2017).

Sectors	Name	A	t-stat	γ_1	t-stat	γ_2	t-stat	Adjusted R^2
1	A01	0.010 ***	(19.21)	0.346 ***	(9.27)	−2.649 ***	(−5.49)	0.065
2	A02	0.007 ***	(21.76)	0.088 ***	(7.99)	−0.050	(−1.49)	0.055
3	A03	0.008 ***	(22.29)	−0.125 ***	(−7.65)	2.662 ***	(20.98)	0.232
4	A04	0.011 ***	(29.95)	−0.036 **	(−2.24)	−2.273 ***	(18.44)	0.244
5	A05	0.009 ***	(16.27)	−0.015	(−0.60)	3.234 ***	(20.85)	0.316
6	B07	0.010 ***	(21.21)	0.119 ***	(3.95)	2.223 ***	(6.23)	0.164
7	B08	0.012 ***	(19.94)	0.019	(0.51)	2.340 ***	(5.26)	0.081
8	B09	0.013 ***	(44.92)	0.061 ***	(4.71)	2.484 ***	(62.95)	0.756
9	B11	0.010 ***	(22.72)	0.026	(1.46)	2.120 ***	(26.37)	0.409
10	C13	0.014 ***	(25.88)	−0.012	(−0.33)	2.808 ***	(6.56)	0.096
11	C14	0.013 ***	(28.46)	0.128 ***	(8.73)	−0.067 ***	(−6.36)	0.072
12	C15	0.014 ***	(58.48)	0.078 ***	(7.86)	1.798 ***	(77.08)	0.839
13	C18	0.016 ***	(49.71)	−0.265 ***	(−18.02)	6.179 ***	(57.24)	0.636
14	C19	0.006 ***	(6.60)	0.415 ***	(7.01)	−4.284 ***	(−6.56)	0.158
15	C20	0.007 ***	(5.48)	0.329 ***	(3.44)	−2.354	(−1.37)	0.216
16	C21	0.011 ***	(9.92)	0.033	(0.53)	6.484 ***	(18.51)	0.835
17	C22	0.013 ***	(10.43)	−0.144	(−1.19)	16.392 ***	(6.88)	0.425
18	C23	0.007 ***	(7.91)	0.146 *	(1.81)	0.752	(0.41)	0.197
19	C24	0.008 ***	(10.51)	0.463 ***	(6.83)	5.617 ***	(16.35)	0.933
20	C25	−0.002	(−0.47)	1.138 ***	(3.50)	−12.514 ***	(−3.01)	0.389
21	C28	0.006 ***	(6.75)	0.309 ***	(3.08)	0.328	(0.12)	0.270
22	C29	0.008 ***	(9.11)	−0.006	(−0.05)	24.212 ***	(5.16)	0.412
23	C32	0.009 ***	(8.78)	0.293 ***	(3.66)	1.232	(0.68)	0.306
24	C33	0.007 ***	(9.34)	0.101	(1.25)	−6.916 ***	(2.89)	0.349
25	C38	0.006 ***	(6.92)	0.201 **	(2.52)	2.854	(1.63)	0.370

Table 5. *Cont.*

26	C40	0.011 ***	(13.11)	0.085	(1.22)	7.396 ***	(4.02)	0.429
27	E47	0.012 ***	(7.46)	−0.062	(−0.44)	−10.440 ***	(4.64)	0.311
28	G53	0.008 ***	(6.80)	0.198	(1.55)	3.351	(0.94)	0.177
29	G58	0.006 ***	(6.56)	0.350 ***	(2.84)	4.851	(1.55)	0.293
30	G59	0.005 ***	(5.61)	0.140	(1.39)	−5.289 **	(2.53)	0.292
31	I63	0.100 **	(6.25)	−1.182	(−1.73)	1.770	(0.25)	0.999
32	I64	0.011 ***	(7.28)	−0.187	(−1.38)	9.974 ***	(5.95)	0.406
33	J66	0.008 ***	(5.05)	0.336 ***	(3.02)	−1.149	(−0.76)	0.175
34	J68	0.009 ***	(7.55)	0.374 ***	(3.95)	−0.938	(−0.74)	0.217
35	J69	0.003 ***	(4.32)	0.310 ***	(5.30)	−3.294 ***	(−4.54)	0.118
36	M74	0.010 ***	(8.93)	−0.126 ***	(−2.71)	3.313 ***	(17.83)	0.779
37	N77	0.006 ***	(5.75)	0.139 **	(2.01)	−0.364	(−0.35)	0.072
38	Q83	0.009 ***	(4.58)	0.487 ***	(4.53)	−5.222 ***	(−4.11)	0.172
39	R85	0.007 ***	(5.03)	0.358 ***	(3.51)	−3.016	(−1.50)	0.174
40	R86	0.009 ***	(7.15)	0.073	(0.89)	0.153	(0.13)	0.062
41	S90	0.007 ***	(15.05)	0.406 ***	(14.59)	−3.765 ***	(−11.00)	0.140

Note: *,**,*** denote test statistics significant at 10%, 5%, and 1% respectively, while p-value in parenthesis.

Table 6. Industry Herding Bias at the SZSE (2008–2017).

Sectors	Codes	α	t-stat	γ_1	t-stat	γ_2	t-stat	Adjusted R^2
1	A01	0.013 ***	(21.15)	−0.017	(−0.44)	3.557 ***	(8.00)	0.120
2	A02	0.013 ***	(28.11)	−0.169 ***	(−7.39)	5.350 ***	(26.80)	0.374
3	A03	0.014 ***	(24.27)	−0.194 ***	(−5.47)	−6.004 ***	(14.77)	0.194
4	A03	0.015 ***	(25.95)	−0.165 ***	(−5.66)	5.456 ***	(23.82)	0.289
5	A04	0.009 ***	(19.35)	0.146 ***	(7.11)	−2.294 ***	(22.28)	0.498
6	A05	0.009 ***	(20.66)	0.135 ***	(4.75)	0.230	(0.65)	0.101
7	B06	0.010 ***	(17.58)	0.027	(1.17)	2.850 ***	(27.75)	0.583
8	B07	0.009 ***	(19.74)	0.135 ***	(5.14)	0.277	(0.92)	0.128
9	B08	0.015 ***	(41.11)	−0.133 ***	(−8.95)	3.841 ***	(36.06)	0.442
10	B09	0.010 ***	(15.89)	0.290 ***	(11.50)	−1.766 ***	(17.41)	0.483
11	B11	0.013 ***	(24.06)	0.265 ***	(7.45)	−2.010 ***	(−4.28)	0.048
12	C14	0.017 ***	(38.17)	−0.288 ***	(−13.19)	7.423 ***	(37.20)	0.456
13	C15	0.014 ***	(50.29)	0.085 ***	(7.26)	1.605 ***	(60.64)	0.772
14	C17	0.016 ***	(38.32)	−0.241 ***	(−9.64)	5.937 ***	(18.97)	0.220
15	C18	0.017 ***	(36.88)	−0.346 ***	(−13.27)	−8.768 ***	(32.78)	0.393
16	C19	0.010 ***	(13.17)	0.132 ***	(4.24)	2.445 ***	(21.73)	0.479
17	C20	0.008 ***	(18.64)	0.240 ***	(15.52)	0.580 ***	(16.69)	0.400
18	C21	0.015 ***	(28.16)	−0.267 ***	(−9.97)	7.089 ***	(31.99)	0.480
19	C22	0.014 ***	(37.79)	0.026 *	(1.80)	−2.708 ***	(41.56)	0.562
20	C23	0.009 ***	(20.55)	0.242 ***	(14.25)	0.872 ***	(18.47)	0.401
21	C24	0.012 ***	(27.95)	−0.025	(−1.49)	2.415 ***	(28.15)	0.362
22	C25	0.011 ***	(23.42)	0.203 ***	(6.53)	−1.012 **	(−2.50)	0.079
23	C26	0.012 ***	(27.52)	0.228 ***	(8.48)	−1.950 ***	(−5.50)	0.083
24	C27	0.016 ***	(57.70)	−0.169 ***	(−15.23)	4.517 ***	(57.08)	0.648
25	C28	0.013 ***	(35.34)	0.035 ***	(2.60)	1.768 ***	(28.25)	0.404
26	C29	0.016 ***	(30.98)	−0.201 ***	(−6.22)	−5.631 ***	(13.92)	0.160
27	C30	0.013 ***	(26.21)	0.173 ***	(5.33)	−0.262	(−0.62)	0.074
28	C31	0.012 ***	(42.43)	−0.054 ***	(−4.68)	2.733 ***	(48.69)	0.599
29	C32	0.017 ***	(37.33)	−0.364 ***	(−14.36)	−6.702 ***	(23.14)	0.231
30	C33	0.016 ***	(45.67)	−0.229 ***	(−14.99)	4.988 ***	(37.94)	0.445
31	C34	0.015 ***	(31.98)	−0.048 *	(−1.70)	2.687 ***	(7.53)	0.101
32	C35	0.013 ***	(24.94)	0.238 ***	(7.44)	−1.675 ***	(−3.93)	0.074
33	C36	0.017 ***	(43.78)	−0.336 ***	(−16.74)	6.796 ***	(31.09)	0.353
34	C37	0.013 ***	(24.17)	0.145 ***	(4.22)	0.892 **	(2.02)	0.098
35	C38	0.016 ***	(9.08)	−0.065	(−0.78)	1.643	(1.34)	0.120
36	C39	0.015 ***	(9.63)	−0.016	(−0.23)	0.795	(0.83)	0.093
37	C40	0.005 ***	(2.80)	0.385 ***	(3.56)	−3.662 ***	(−2.88)	0.115
38	C41	0.012 ***	(8.48)	−0.132 **	(−2.41)	3.585 ***	(14.31)	0.734
39	D44	0.009 ***	(23.58)	0.277 ***	(11.66)	−1.954 ***	(−6.31)	0.150

Table 6. *Cont.*

40	D45	0.012 ***	(27.78)	−0.234 ***	(−10.49)	5.519 ***	(29.77)	0.380
41	E47	0.011 ***	(25.96)	−0.086 ***	(−4.64)	−3.734 ***	(29.33)	0.379
42	E48	0.018 ***	(41.11)	−0.343 ***	(−15.49)	7.722 ***	(35.95)	0.420
43	E50	0.011 ***	(22.07)	0.059 ***	(2.69)	3.498 ***	(29.80)	0.511
44	F51	0.011 ***	(25.41)	0.172 ***	(6.33)	−0.717 **	(−2.02)	0.112
45	F52	0.009 ***	(22.78)	0.295 ***	(10.41)	−1.831 ***	(−4.77)	0.145
46	G54	0.012 ***	(31.35)	−0.210 ***	(−9.14)	5.300 ***	(20.95)	0.262
47	G55	0.015 ***	(32.84)	−0.340 ***	(−13.52)	7.214 ***	(28.44)	0.329
48	G56	0.003 ***	(9.47)	0.402 ***	(16.24)	−3.627 ***	(−11.78)	0.142
49	G58	0.009 ***	(20.42)	0.099 ***	(5.15)	2.301 ***	(27.36)	0.515
50	G59	0.014 ***	(26.77)	−0.279 ***	(−10.23)	8.040 ***	(41.49)	0.702
51	H61	0.009 ***	(20.28)	0.122 ***	(4.39)	0.056	(0.17)	0.117
52	H62	0.009 ***	(21.74)	0.038 **	(2.48)	−1.786 ***	(35.00)	0.533
53	I63	0.017 ***	(29.84)	−0.160 ***	(−5.32)	5.971 ***	(20.80)	0.268
54	I64	0.017 ***	(27.86)	−0.302 ***	(−8.57)	−8.097 ***	(19.40)	0.277
55	I65	0.016 ***	(32.24)	−0.159 ***	(−5.34)	4.849 ***	(13.62)	0.159
56	J66	0.006 ***	(14.54)	0.069 ***	(3.78)	−2.773 ***	(25.33)	0.468
57	J67	0.008 ***	(17.71)	0.013	(0.44)	1.683 ***	(4.85)	0.086
58	K70	0.008 ***	(22.90)	0.230 ***	(12.03)	−1.877 ***	(−7.54)	0.231
59	L72	0.012 ***	(23.34)	0.195 ***	(5.55)	0.220	(0.48)	0.093
60	M73	0.009 ***	(11.10)	−0.031	(−0.86)	3.165 ***	(17.90)	0.553
61	M74	0.014 ***	(27.28)	−0.166 ***	(−7.08)	5.986 ***	(32.69)	0.458
62	N77	0.007 ***	(11.05)	0.370 ***	(14.80)	0.428 ***	(5.72)	0.332
63	Q83	0.009 ***	(16.25)	0.089 ***	(4.55)	1.820 ***	(32.97)	0.730
64	R85	0.012 ***	(19.27)	−0.048 *	(−1.96)	2.732 ***	(24.70)	0.472
65	R86	0.006 ***	(7.92)	0.484 ***	(19.38)	−0.284 ***	(−5.14)	0.279
66	R87	0.006 ***	(4.56)	0.165 ***	(2.88)	1.690 ***	(9.42)	0.803
67	S90	0.008 ***	(20.87)	0.036 **	(2.42)	2.183 ***	(30.38)	0.456

Note: *,**,*** denote test statistics significant at 10%, 5%, and 1% respectively, while p-value in parenthesis.

4.3. Firm-Level Herding Bias

4.3.1. IHR Bias

Table 7 reports the dummies oftheIHR index among 667 and 379 traded firms of SSE and SZSE, respectively, and favors the hypothesis 2 [28,38,56]. The proportion of holding IHR, dummy 1, among traded firms varies with respect to time and more variation in IHR seems at SZSE, i.e., minimum 7% to maximum 13% during the sample periods.

Table 7. Investors Herding (IHR) index at the SSE and SZSE (2008–2017).

Year	SSE		SZSE	
	Total of 664 A-shares		Total of 379 A-shares	
	1	0	1	0
2008	56	608	51	328
2009	63	601	39	340
2010	66	598	25	354
2011	62	602	46	333
2012	60	604	49	330
2013	56	608	47	332
2014	59	605	45	334
2015	64	600	47	332
2016	63	601	32	347
2017	58	606	58	339

Source: Authors' own research, 2019.

4.3.2. MHR Bias

Table 8 demonstrates that the managers of A-shares listed firms at the SZSE appear more likely to follow their peers in their investment decisions. The average proportion of existence MHR, dummy 1, is 34% and 35%, varies from 31% to 38% and 31% to 39% at the SSE and SZSE, respectively. Minimum ratio of holding MHR appears in 2008 and 2010, while the maximum evidence of MHR looks at 2016 and 2012 at the SSE and SZSE, respectively. Table 8 provides a snapshot of IHR and MHR indices among listed firms of the SSE and SZSE for the said sample period.

Table 8. Managers herding (MHR) Index at the SSE and SZSE (2008–2017).

Year	(SSE)		(SZSE)	
	Total of 664 A-shares		Total of 379 A-shares	
	1	0	1	0
2008	209	455	135	244
2009	230	434	143	236
2010	229	435	118	261
2011	218	446	135	244
2012	235	429	146	233
2013	210	454	135	244
2014	230	434	140	239
2015	234	430	130	249
2016	242	422	124	255
2017	220	444	122	257

Source: Authors' own research, 2019.

Bars in Figure 1 explain the increase, decrease and non-monotonic relation between IHR and MHR. At the SSE, both the IHR and MHR both increase in 2008, 2014 and 2015, decreases in 2011, 2013 and 2017. Likewise, both the IHR and MHR at the SZSE both increase in 2008, 2011 2012, and decrease in 2010, 2013 and 2016, the rest of the years show a different trend between IHR and MHR.

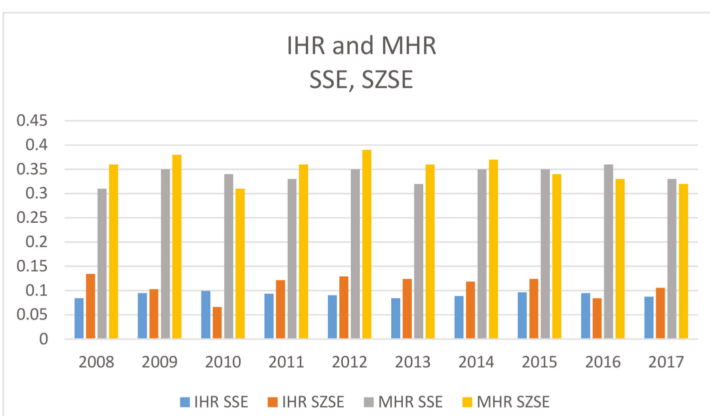

Figure 1. IHR and MHR percentages associated with listed firms of 664-SSE and 379-SZSE. Source: Authors' own research, 2019.

Figure 2 explains the versatile trading behavior of Chinese investors during the sample periods. In this figure, the period of 2013 to 2017 seems to be a highly volatile period of both of the markets where the trading index has divergent experiences.

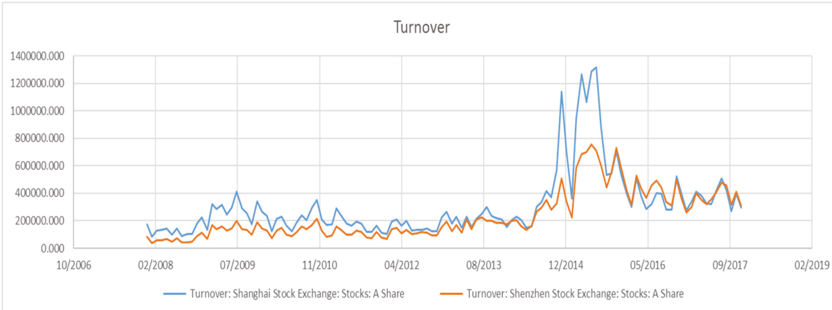

Figure 2. Turnover of A-Shares at SSE and SZSE: Source; CEIC Data. Source: Authors' own research, 2019.

4.4. Herding Bias and Firm Value

Impact of IHR and MHR on FV is analyzed through multivariate regression with respect to hypotheses 3 to 5. In Table 9, Table 10, Table 11, Table 12, we use the market to book value as the proxy of FV, which is explained in Table 1.The Hausman test guides us to use the fixed effect regression analysis, which assumes a rejection of the random effect hypothesis under a significant p-value. Hence, we reject the null hypothesis, the random effect is appropriate. Using the following Equations (11)–(13), fixed-effect regression analysis with industries and time dummies reports result in Table 9, Table 10, Table 11, Table 12.

$$FV_t = \beta_0 + \beta_1 IHR_t + \beta_2 CF_t + \beta_3 FS_t + \beta_4 FL_t + \beta_5 FG_t + \gamma + \mu + \epsilon \quad (11)$$

$$FV_t = \beta_0 + \beta_1 MHR_t + \beta_2 CF_t + \beta_3 FS_t + \beta_4 FL_t + \beta_5 FG_t + \gamma + \mu + \epsilon \quad (12)$$

$$FV_t = \beta_0 + \beta_1 IHR_t + \beta_2 MHR_t + \beta_3 IHR_t{*}MHR_t + \beta_4 CF_t + \beta_5 FS_t + \beta_6 FL_t + \beta_7 FG_t + \gamma + \mu + \epsilon \quad (13)$$

Table 9, a fixed effect regression model with year and industry dummies illustrates the impact of IHR, MHR and their interaction (IHR*MHR) on FV at the listed firms of the SSE and SZSE under the full sample period. The results support the third hypothesis in both of the markets, which implies that IHR positively drives the FV ceteris paribus. Whereas, the fourth and fifth hypotheses based on MHR hold true at the SZSE, where MHR and interaction demonstrate the positive impact on the FV. Overall findings document the influence of herding bias upon the FV, which gains support by prior literature [6,12,22]. However, the strength of relation exists insignificant during the sample period. To further diagnose the intensity of the said relation, we revisit the sample and select the extreme trading period of A-shares in line with the related literature [16,28], based upon the turnover of shares at the SSE and the SZSE. Table 10 presents the result of IHR, MHR and their interaction on the FV from 2013 to 2017, a highly divergent period, shown in Figure 2 of A-shares trading at the SSE and SZSE.

The results in Table 10 reveal that herding bias derives the FV at the SSE and SZSE. It explains that FV at the SSE is adversely affected by the MHR at the 5% level of significance with t-value (2.03). Whereas, at the SZSE, herding bias positively derives the FV, and this impact seems to be more profound by the IHR, i.e., 10% significance with a t-value (1.68). Further, CF significantly increases among those firms that are positively influenced by the interaction of IHR and MHR, while FG is positively and significantly caused by negative interaction of herding biases. On the other hand, FS shows the negative and significant impact on the FV regardless of the magnitude of interaction. FL explains the positive impact on FV among the listed firms of both the markets. Results of control variables are consistent with prior literature [57,58]. The results support the third and fifth hypotheses of the study only at the SZSE, and contradict all hypotheses at the SSE. The reason for controverting findings from the prior literature, specifically at the SSE, might be due to the high and sharp shift in trading behavior from boom to slump. To capture the impact of this relation at a specific time interval, we divide the subsample into annual and bi-annual periods, based on a sharp, shifty, yearly edge turnover of A-shares.

Table 9. MHR, and firm value (FV) (2008–2017).

VARIABLES	SSE			SZSE		
	(1)	(2)	(3)	(4)	(5)	(6)
	MB	MB	MB	MB	MB	MB
IHR	0.033			0.072		
	(0.49)			(0.86)		
MHR		−0.063			0.032	
		(−1.52)			(0.57)	
IHR*MHR			−0.166			0.059
			(−1.19)			(0.33)
CF	0.459 **	0.459 **	0.463 **	1.362 ***	1.355 ***	1.359 ***
	(2.26)	(2.26)	(2.28)	(5.03)	(5.01)	(5.02)
FL	−0.030 ***	−0.030 **	−0.030 **	−0.036 *	−0.036 *	−0.037 *
	(−2.59)	(−2.55)	(−2.54)	(−1.94)	(−1.93)	(−1.95)
FG	−0.035 *	−0.034 *	−0.034 *	0.031	0.031	0.031
	(−1.88)	(−1.82)	(−1.82)	(1.16)	(1.16)	(1.15)
FS	−0.672 ***	−0.672 ***	−0.672 ***	−0.708 ***	−0.709 ***	−0.709 ***
	(−30.44)	(−30.41)	(−30.42)	(−23.81)	(−23.80)	(−23.81)
Constant	17.185 ***	17.172 ***	17.162 ***	17.063 ***	17.062 ***	17.071 ***
	(42.83)	(42.80)	(42.76)	(28.15)	(28.14)	(28.14)
Observations	6640	6640	6640	3790	3790	3790
R-squared	0.354	0.355	0.355	0.329	0.329	0.330
Adj. R^2	0.346	0.347	0.347	0.318	0.318	0.318
F-Stat	43.91	43.95	42.92	29.05	29.04	28.15
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes
Ind. Effect	Yes	Yes	Yes	Yes	Yes	Yes

Note: *,**,*** denote test statistics significant at 10%, 5%, and 1%, respectively,while the *p*-value is in parentheses. Where MB = FV measured market to book value of assets, IHR = investor herding, MHR = managers herding, CF = cash flow, FL= firm leverage, FG = firm growth, FS = firm size.Source: Authors' own research, 2019.

Table 10. MHR, and FV (2013–2017).

VARIABLES	SSE			SZSE		
	(1)	(2)	(3)	(4)	(5)	(6)
	MB	MB	MB	MB	MB	MB
IHR	−0.028			0.127 *		
	(−0.16)			(1.68)		
MHR		−0.218 **			−0.059	
		(−2.03)			(−0.65)	
IHR*MHR			−0.196			0.136
			(−0.53)			(0.46)
CF	0.516	0.526	0.528	1.160 ***	1.161 ***	1.177 ***
	(0.98)	(1.00)	(1.01)	(2.69)	(2.69)	(2.72)
FL	0.042	0.045	0.045	0.028	0.028	0.027
	(1.40)	(1.48)	(1.50)	(0.92)	(0.92)	(0.91)
FG	0.089 *	0.092 *	0.093 *	−0.023	−0.020	−0.022
	(1.81)	(1.88)	(1.89)	(−0.52)	(−0.47)	(−0.50)
FS	−0.965 ***	−0.963 ***	−0.964 ***	−0.712 ***	−0.710 ***	−0.711 ***
	(−16.68)	(−16.66)	(−16.66)	(−15.12)	(−15.04)	(−15.06)
Constant	20.731 ***	20.664 ***	20.655 ***	18.233 ***	18.158 ***	18.210 ***
	(19.95)	(19.89)	(19.87)	(19.14)	(19.06)	(19.08)
Observations	3320	3320	3320	1895	1895	1895
R-squared	0.200	0.201	0.201	0.323	0.323	0.323
Adj. R^2	0.181	0.182	0.181	0.302	0.301	0.301
F-Stat	10.52	10.59	10.32	15.10	15.08	14.59
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes
Ind. Effect	Yes	Yes	Yes	Yes	Yes	Yes

Note: *,**,*** denote test statistics significant at 10%, 5%, and 1%, respectively, while their *p*-value is in parentheses. Where MB = FV measured market to book value of assets, IHR = investor herding, MHR = managers herding, CF = cash flow, FL = firm leverage, FG = firm growth, FS = firm size.Source: Authors' own research, 2019.

4.4.1. IHR, MHR, and FFP During Economic Shocks

Table 11 reports the impact of IHR and MHR on FV during the economic shocks, as an exogenous factor, we divide the sub-sample into four intervals, i.e., 2013, 2014–2015, 2016, 2017, annually and bi-annually based on the turnover trend shown inFigure 2. Among these four intervals, second interval, 2014–2015, is bi-annual, as this period contains the versatile trading behavior, bottom-peak-bottom, of the index. Thefirst interval 2013 is in a less volatile period of A-shares at both the markets. During this year, IHR negatively influences the FV, while MHR positively influenced the FV at the SSE and SZSE, respectively. The interaction term explains the positive relation with FV, and this relation seems 10% significant at the SZSE. The second interval 2014–2015 shows the extreme trading behavior of A-shares at both the market where the SSE seems more volatile relative to the SZSE. Over this period, IHR exhibits a positive and significant effect on the FV, while MHR significantly and negatively influences the FV. Apparently, FV at SSE seems to be more sensitive towards the IHR, whereas, at the SZSE, IHR and MHR both significantly drive the FV with a 90% level of confidence. The interaction term explains that in the extreme trading period, IHR and MHR negatively influenced the FV.

The results in 2016, the immediate year after the highest and the lowest market index in 2015, capture the effects of the aftershocks. Market movement over this year quarterly moves up and down and explains the negative impact of IHR and MHR on the FV at both markets. The interaction term explains the mixed results at both the SSE and SZSE, respectively.

The last interval (2017), is relatively low volatile, compared with second and third interval, which explains the negative and positive impact of IHR and its interaction term on FV at the SSE and SZSE, respectively. However, MHR clarifies a negative and positive impact on FV at the SSE and SZSE.

Theoverall finding over the four intervals demonstrates that IHR and MHR strongly appears, and interactively negatively derives the FV during the extreme market movements. Whereas, in the low volatile period, the significance disappears, and the negative interactive effect on the FV at SSE continues as aftereffects. We also capture the impact of herding bias during the said sample in the group of industries listed at the SSE and SZSE. For this purpose, we rearrange our sample based on the group A-industry classification cited in the CSMAR database. Table 12 describes the results of industries and market wise relation of herding bias with FV.

Table 11. IHR, MHRand FV during economic shocks.

VARIABLES	2013		2014–2015		2016		2017	
	(1)	**(3)**	**(3)**	**(3)**	**(3)**	**(4)**	**(5)**	**(6)**
	SSE	**SSE**	**SSE**	**SZSE**	**SSE**	**SZSE**	**SSE**	**SZSE**
	MB	**MB**	**MB**	**MB**	**MB**	**MB**	**MB**	**MB**
IHR	−0.301	−0.233	0.360 ***	0.327 **	−0.159	−0.198	−0.097	0.344
	(−1.30)	(−0.90)	(2.78)	(2.41)	(−0.70)	(−0.68)	(−0.44)	(1.24)
MHR	0.031	0.217	−0.143 *	−0.201 **	−0.048	−0.074	0.142	0.269
	(0.22)	(1.21)	(−1.73)	(−2.26)	(−0.34)	(−0.42)	(1.07)	(1.46)
IHR*MHR	0.240	0.921 *	−0.135	−0.188	−0.124	0.003	−0.220	0.748
	(0.47)	(1.65)	(−0.49)	(−0.65)	(−0.27)	(0.00)	(−0.41)	(1.21)
Observations	1707	1422	1707	1422	1707	1422	1707	1422
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Source: Authors' own research, 2019.

4.4.2. Group A-Industry Classification

Table 12 presents the relation of herding bias on the FV at the SSE and SZSE among six groups of industries (Group A-industry classification). Empirical results show that IHR positively and significantly derives the FV at the SZSE in the industry group. While MHR explains the negative and significant impact on the FV under the same industry head. However, the interaction term of IHR and

MHR exhibits positive impact on FV at the SSE and SZSE, respectively. Likewise, MHR also has a positive significant effect on FV between the Business and Financial sector at the SZSE. The significant impact of MHR on FV at the SZSE is relatively more pronounced than the SSE. IHR and MHR among other sectors explain the mixed on the FV.

Table 12. Interactive impact of IHR and MHR on FV among Industry Group A.

Groups	SSE			SZSE			SSE		SZSE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	IHR	MHR	IHR * MHR	IHR	MHR	IHR * MHR	Adj. R^2	F-Stat	Adj. R^2	F-Stat
Comprehensive	−0.276 (−0.60)			−1.148 (−1.59)			0.388	17.98	0.615	16.67
		−0.145 (−0.44)			−0.152 (−0.25)		0.387	17.93	0.594	15.32
			−1.298 (−1.18)			0.817 (0.40)	0.386	13.04	0.600	11.49
Utilities	−0.143 (−0.49)			−0.704 (−1.37)			0.294	40.39	0.222	19.48
		0.158 (0.95)			−0.003 (−0.01)		0.295	40.58	0.212	18.99
			−0.597 (−0.98)			−1.472 (−1.19)	0.293	29.11	0.218	16.95
Business	0.264 (1.24)			0.213 (0.43)			0.391	47.06	0.008	12.06
		0.014 (0.11)			0.512 * (1.95)		0.388	46.55	0.103	11.89
			−0.352 (−0.77)			0.781 (0.37)	0.388	33.57	0.100	11.72
Financial	−0.013 (−0.02)			−1.008 (−0.64)			0.508	10.10	0.306	12.23
		0.828 (1.57)			1.594 * (1.87)		0.538	11.22	0.479	13.56
			−0.157 (−0.12)			−0.170 (−0.43)	0.514	7.63	0.628	14.93
Industry	0.030 (0.22)			0.297 ** (2.27)			0.258	137.16	0.260	112.18
		−0.149 * (−1.79)			0.023 (0.26)		0.260	138.01	0.258	110.80
			0.128 (0.45)			0.228 (0.80)	0.259	98.53	0.260	80.18
Real estate	0.051 (0.23)			−0.034 (−0.06)			0.331	35.53	0.321	16.59
		−0.004 (−0.04)			−0.125 (−0.33)		0.331	35.52	0.323	16.62
			−0.517 (−1.07)			1.899 (1.63)	0.329	25.48	0.331	15.16

t-statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Source: Authors' own research, 2019.

5. Conclusions

The literature on herding biases is confined to detection at the aggregate firms, sector/industry, and market level. The study adds to the behavioral finance literature by addressing the surprisingly unnoticed phenomena of the behavioral impact of herding bias on FV at the firm level, using the sample of 1,043 A-Shares listed firms at the SSE and SZSE under fixed effect specification. Initially, we detect the existence of IHR and MHR biases at firm-level applying a CSAD model [15,35] and an investment model of firms' investment absolute deviation approach [6,22]. After such detection, we deploy the panel fixed-effect model with industry and years dummies to investigate the effect of: (1) IHR on FV, (2) MHR on FV and (3) interaction of IHR, and MHR on the FV respectively.

The empirical results document the presence of IHR and MHR bias at market, sector and firm-level in both equity markets, which potentially drive the FV, while the impact is more pronounced during the extreme trading period i.e., 2014 to 2015. The findings are robust under different time intervals and industry classification, and therefore, offers useful policy implications to understand the behavioral dynamics of investors and managers.

Given the vital role of finance in economic sustainability, the study adds invaluable inputs for policy formulation [59,60], specifically, the findings appear to be important for potential investors, as the firm-level financial information is more relevant to their decision, rather relying on an index. Specifically, we infer that the negative interaction of IHR with MHR results in a bullish trend to the stock markets, while the bearish trend is explained by the positive interaction of IHR and MHR. The probability of a market crash may become higher in those circumstances when both negative IHR and MHR interact with each other and cause the FV to decline. Furthermore, this study infersthat at the SSE, if IHR and MHR shift from insignificance to positive significance, it might be the signal of a sudden boom in the market. Whereas, at the SZSE, this suggests that when a positive and significant impact of IHR disappears with the negative impact of MHR, this might be the reason for the sudden decline in trading activity, and vice versa. Thus, the study facilitates to understand the herding biases associated with the investment decisions of investors and managers and their impact on the FV that help corporate stakeholders, financial analysts and stock market regulators to devise their strategic and regulatory policies accordingly.

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Fake News and Propaganda: Trump's Democratic America and Hitler's National Socialist (Nazi) Germany

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Abstract: This paper features an analysis of President Trump's two State of the Union addresses, which are analysed by means of various data mining techniques, including sentiment analysis. The intention is to explore the contents and sentiments of the messages contained, the degree to which they differ, and their potential implications for the national mood and state of the economy. We also apply Zipf and Mandelbrot's power law to assess the degree to which they differ from common language patterns. To provide a contrast and some parallel context, analyses are also undertaken of President Obama's last State of the Union address and Hitler's 1933 Berlin Proclamation. The structure of these four political addresses is remarkably similar. The three US Presidential speeches are more positive emotionally than is Hitler's relatively shorter address, which is characterised by a prevalence of negative emotions. Hitler's speech deviates the most from common speech, but all three appear to target their audiences by use of non-complex speech. However, it should be said that the economic circumstances in contemporary America and Germany in the 1930s are vastly different.

Keywords: text mining; sentiment analysis; word cloud; emotional valence

JEL Classification: C19; C65; D79

1. Introduction

President Trump continues to attract controversy in the media and in political commentary, partly because of his attitude to "fake news", combined with his own lavish use of his Twitter account and lack of attention to the verification of some of his more extreme pronouncements. In 2018, the President used Twitter to announce the "winners" of his "fake news" awards, most frequently naming the New York Times and CNN for a series of perceived transgressions which varied from minor errors by journalists on social media to news reports that later invited corrections.

Given his predilection for criticising the media, the authors have previously analysed his pronouncements on climate change [1], on nuclear weapons and [2], and contrasted his first State of the Union Address (SOU) with the previous one by President Obama [3].

Given the controversy about the timing and delivery of his most recent SOU address, the authors thought it might be of interest to subject both of his SOU addresses to textual analysis using data mining techniques, so as to explore whether his political addresses are typical or whether they deviate markedly from those of other political leaders, specifically, Obama and Hitler, the latter being selected as an extreme benchmark. The null hypothesis is that political speeches are essentially similar.

We decided to analyse both Trump's 2018 State of the Union Address (SOU1), and 2019 address (SOU2) to assess whether there had been any change in the structure and emotional tenor of his two addresses in response to changing political and economic circumstances, at the end of the second year of his term in office. To provide a contrast, one contemporary and another more historically extreme, we also analyse President Obama's last SOU and Hitler's 1933 Berlin Proclamation.

The contents of these speeches are analysed using a variety of R packages, including several in data mining: "tm" a text mining package, created by Feinerer and Hornik [4]. We also used "syuzhet", a sentiment extraction tool, originally developed in the NLP group at Stanford University, and then incorporated into an R package by Jockers [5], and "wordcloud" by Fellows [6].

Data mining refers to the process of analysing datasets to reveal patterns, and usually involves methods that are drawn from statistics, machine learning, and database systems. Text data mining similarly involves the analysis of patterns in text data. Sentiment analysis is concerned with the emotional context of a text, and seeks to infer whether a section of text is positive or negative, or the nature of the emotions involved. There is a variety of methods and dictionaries that exist for undertaking sentiment analysis of a piece of text.

Although sentiment is often framed in terms of being a binary distinction (positive versus negative), it can also be analysed in a more nuanced manner. We decided to apply the R package "syuzhet", which distinguishes between eight different emotions, namely trust, anticipation, fear, joy, anger, sadness, disgust and surprise. There are many different forms of sentiment analyses, but most use the same basic approach. They begin by constructing a list of words or dictionary associated with different emotions, count the number of positive and negative words in a given text, and then analyse the mix of positive and negative words to assess the general emotional tenor of the text.

Clearly, there are considerable limitations to the basic approach adopted in the paper. Pröllochs et al. [7] discussed the difficulties in processing negations, which invert the meanings of words and sentences. Equally problematic are sarcasm, backhanded compliments, and inflammatory gibberish, such as "Pocahontas" and "Crooked Hillary", in the context of President Trump's tweets. Nevertheless, sentiment analysis can reveal the general emotional direction of a piece of text, and machine-based learning systems are well-established methods for the sifting and interpretation of digital information. This tool has numerous applications in, for example, financial markets.

We can now apply machine learning techniques to news feeds to determine what average opinion is. For example, the Thomson Reuters News Analytics (TRNA) series could be termed news sentiment, and is produced by the application of machine learning techniques to news items. The TRNA system can scan and analyse stories on thousands of companies in real time, and translate the results into a series that can be used to help model and inform quantitative trading strategies. RavenPack is another example of a commercial news analytics product that has applications to financial markets. There is now considerable evidence about the commercial relevance of financial news analysed using machine learning methods.

Allen, McAleer and Singh [8,9] analysed the economic impact of the TRNA sentiment series. The first of these papers examines the influence of the Sentiment measure as a factor in pricing DJIA constituent company stocks in a Capital Asset Pricing Model (CAPM) context. The second uses these real time scores, aggregated into a DJIA market sentiment score, to analyse the relationship between financial news sentiment scores and the DJIA return series, using entropy-based measures. Both studies find that the sentiment scores have a significant information component which, in the former, is priced as a factor in an asset pricing context.

Allen, McAleer and Singh [10] used the Thomson Reuters News Analytics (TRNA) dataset to construct a series of daily sentiment scores for Dow Jones Industrial Average (DJIA) stock index constituents. The authors used these daily DJIA market sentiment scores to study the influence of financial news sentiment scores on the stock returns of these constituents using a multi-factor model. They augmented the Fama–French three-factor model with the day's sentiment score along 20 with lagged scores to evaluate the additional effects of financial news sentiment on stock prices in the context of this model. Estimation is based on Ordinary Least Squares (OLS) and Quantile Regression (QR) to analyse the effects around the tails of the returns distribution. The results suggest that, even when market factors are taken into account, sentiment scores have a significant effect on Dow Jones constituent returns, and that lagged daily sentiment scores are also often significant.

Other research on this topic argues that news items from different sources influence investor sentiment, which feeds into asset prices, asset price volatility and risk (see, among others, Tetlock [11] Tetlock, Macskassy and Saar-Tsechansky [12] (2008), Da, Engleberg and Gao, [13], Barber and Odean [14], diBartolomeo and Warrick [15], Mitra, Mitra and diBartolomeo [16], and Dzielinski, Rieger and Talpsepp [17]. The diversification benefits of the information impounded in news sentiment scores provided by RavenPack were demonstrated by Cahan, Jussa and Luo [18], and Hafez and Xie [19], who examined the benefits in the context of popular asset pricing models.

Several papers provide surveys of this burgeoning literature. Kearney and Lui [20] concentrated on sentiment analysis and provided an analysis of methods and the related literature. Loughran and McDonald [21] provided a survey of the accounting, finance, and economics literature on textual analysis, plus a description of some of its methods, together with potential pitfalls in its application.

In the current paper, the focus is on the actual content of President Trump's 2018 SOU1, and his subsequent 2019 SOU2 address. The intention is to explore whether there are any systematic differences in the sentiments of these two SOUs, and whether there is any evidence of a tendency by President Trump to generate a "positive" spin for the benefit of his voter base. A contrast is provided by parallel analyses of President Obama's last SOU and Hitler's 1933 Berlin Proclamation.

Could President Trump's addresses be fairly described as constituting "propaganda"? This has been defined as being the presentation of information, ideas, opinions, or images, which may only present one part of an argument, and which are broadcast, published, or in some other way spread with the intention of influencing people's opinions. Sentiment analysis will not give a clear answer as to whether content represents propaganda per se, but it will give an indication as to the emotional tenor of a text or speech. It will reveal correlations between the use of words, changes in sentiment, and any patterns revealed through time in the presentation of a speech.

An alternative approach to the analysis of language as a whole, was first suggested by Zipf (1932, p. 1) [22], who applied a concept of relative frequency which suggested that: "the accent or degree of conspicuousness of any word, syllable, or sound is inversely proportionate to the relative frequency of that word, syllable, or sound, among its fellow words, syllables, or sounds in the stream of spoken language. As any element's usage becomes more frequent, its form tends to become less accented, or more easily pronounceable, and vice versa. He analysed whether the modern vernacular of Beijing, China, was consistent with Indo-European tongues in substantiating his "Principle of Relative Frequency".

Zipf [22] suggested that there are four important characteristics that are recognisable in words: The first is meaning, an elusive concept which is difficult to describe. The second he described as being "quality", by which he meant positive or negative qualities. These are the subject of sentiment analysis in the current paper. The third he described as being "emotional intensity", which could also be related to the degree to which sentiment is espoused. The fourth he described as being "order", which is related to semantic change and the relative frequency of use of different words. Order is also related to the probability of occurrence of different words. Zipf suggested that the formula for abbreviation is $ab^2 = k$.

Mandelbrot [23] expanded on this approach, refining Zipf's theory by suggesting that human languages evolved over time to optimise the capacity to convey information from the sender to receiver. He couched his analysis in terms of Shannon's [24] "information theory". Mandelbrot suggested that, as a first approximation, $i(r,k)/k$,which he defines as the relative number of repetitions of the word $W(r)$ in a sample of length k, is inversely proportional to 10 times r, $i(r,k)/k = 1/10r$.

Shannon ([24], p. 6) suggested that it is possible to use artificial languages to approximate natural languages. The zero-order approximation is to choose all letters with the same probability and independently. The first-order approximation is to choose each letter independently but with the same probability of occurrence as would apply in the relevant natural language. In a third-order approximation, a trigram structure is adopted with the probability of each letter dependent on the preceeding two letters.

Shannon [24] suggested that we let $p(B_i)$ be the probability B_i of a sequence of symbols from a source text. Let:

$$G_N = -\frac{1}{N}\sum_i p(B_i) log p(B_i), \tag{1}$$

where the sum is over all sequences B_i containing N symbols. This suggests that G_N is a monotonically decreasing function of N, and that:

$$\underset{N\to\infty}{Lim}\, G_N = H.$$

Shannon lets $p(B_i, S_j)$ be the probability of sequence B_i being followed by symbol S_j and $p_{B_i}S_j = p(B_i, S_j)/p(B_i)$ be the conditional probability of S_j after B_i. Then, let:

$$F_N = -\sum p(B_i, S_j) log p_{B_i}(S_j), \tag{2}$$

where the summation is over all blocks B_i of $N-1$ symbols and over all symbols S_j; then, F_N is a monotonically decreasing function of N :

$$F_N = NG_N - (N-1)G_{N-1},$$

$$G_N = \frac{1}{N}\sum_{N=1}^{N} F_N,$$

$$F_N \leq G_N,$$

and, $Lim_{N\to\infty} F_N = H$.

Shannon [24] stated that F_N is the entropy of the Nth-order approximation to the source of the type discussed above. Mandelbrot [23] suggested that his derivation of the law of word frequencies was characterised by maximising Shannon's "quantity of information" under certain constraints.

We use some of these concepts in the subsequent analysis of the political addresses featured in this paper to explore how far they deviate from standard patterns of language. The most recent comprehensive use of this type of analysis is that of Ficcadenti et al. [25], which also features a lengthy review of the relevant literature. However, there is no sentiment analysis of Presidential speeches in their study.

The remainder of the paper is divided into four sections. An explanation of the research method is given in Section 2. Section 3 presents the results. Section 4 provides some concluding comments.

2. Research Method

The analysis features the use of a number of R libraries which facilitate data mining and sentiment analysis, namely word cloud, tm and syuzhet, plus a variety of graphics packages. The R package tm has a focus on extensibility based on generic functions and object-oriented inheritance, and provides a basic infrastructure required to organise, transform, and analyse textual data. The basic document is imported into a "corpus", which is then transformed into a suitable form for analysis using stemming, stopword removal, and so on. Then, we can create a term-document matrix from a corpus which can be used for analysis.

Once we have the text in matrix form, a huge amount of R functions (e.g., clustering, classifications, among others) can be applied. We can explore the associations of words, correlations, and so forth, and screen the text for frequently occurring words. The analysis can be used to create a word cloud of the most frequently used words. Feinerer and Hornik [4] provided an introduction to the package.

The R package wordcloud by Fellows [6] provides functionality to create word clouds, visualise differences and similarity between documents, and avoid over-plotting in scatter plots with text. We use the R package "syuzhet" for sentiment analysis. The package comes with four sentiment dictionaries, and provides a method for accessing the robust, but computationally expensive, sentiment extraction tool developed in the NLP group at Stanford University. We transform the text in character vectors. Once we have the vector, we can select which of the four sentiment extraction methods available in "syuzhet" to employ. We use the default syuzet lexicon, which was developed in the Nebraska Literary Lab under the direction of Jockers [5].

The name "Syuzhet" comes from the Russian Formalists Shklovsky [26] and Propp [27], who divided narrative into two components, the "fabula" and the "syuzhet". "Syuzhet" refers to the "device" or technique of a narrative, whereas "fabula" is the chronological order of events. 'Syuzhet", therefore, is concerned with the manner in which the elements of the story (fabula) are organised (syuzhet). The R syuzhet package attempts to reveal the latent structure of narrative by means of sentiment analysis, and we can construct global measures of sentiment into eight constituent emotional categories, namely trust, anticipation, fear, joy, anger, sadness, disgust and surprise.

While these global measures of sentiment can be informative, they tell us very little in terms of how the narrative is structured and how these positive and negative sentiments are activated across the text. To explore this, we plot the values in a graph where the x-axis represents the passage of time from the beginning to the end of the text, and the y-axis measures the degrees of positive and negative sentiment.

President Trump's first SOU in 2018 contained 5169 words and 30,308 characters, while his second SOU in 2019 contained 5493 words and 32,204 characters. Therefore, the two addresses were of similar size.

We use the R package "tm" and develop the appropriate R code to undertake the Zipf and Mandelbrot power law distribution analysis to assess the degree to which the four political addresses deviate from common language.

The limitations of the analysis should be borne in mind. The context of "natural language processing", of which sentiment analysis is a component, is important. The use of sarcasm and other types of ironic language are inherently problematic for machines to detect, especially when viewed in isolation.

3. Results and Interpretation of the Analysis

3.1. Sentiment Analysis

Figure 1 presents a word cloud analysis of President Trump's two SOUs. In his first 2018 SOU, depicted in Figure 1A, the most frequently occurring word is "American", followed by the symbol *a€*•, which is a generic representation of different dollar amounts mentioned at various stages in his address. Other words emphasised include "will", "year", "one", "tonight", "people", "new", "year", "america", "together", 'great", "home", "tax" "congress", "families", "countries", "proud", "just", "job", and "citizen".

The second and most recent SOU by President Trump is shown in Figure 1B. This is dominated by the words "will", "American", "years", "one", "new", "thank", "americans", "tonight", "now", "can", 'must", "congress", "border", "last", "time", "also", and "country".

(**A**)

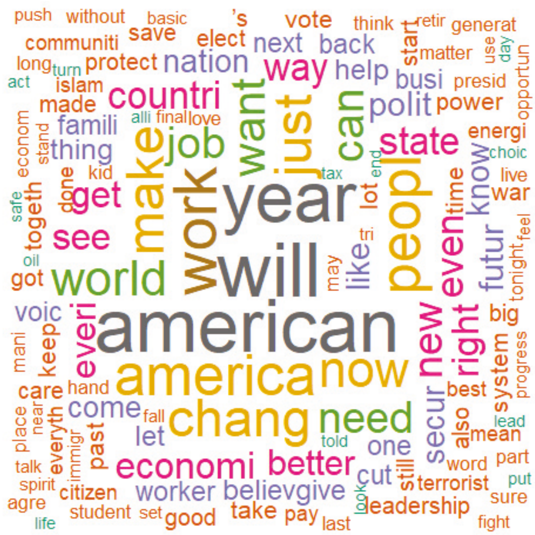
(**B**)

Figure 1. Word Cloud representing President Trump's two SOU addresses: (**A**) Word Cloud SOU2018; and (**B**) RplotTRUMPSOU1CLOUD. The aϵ is a symbol representing different dollar amounts.

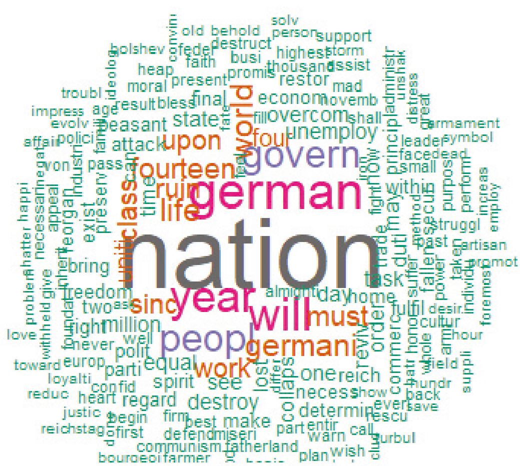
To provide a further contrast, the authors thought it might be instructive to compare this SOU with President Obama's last SOU. Moreover, to provide an extreme contrast, we undertook an analysis of Hitler's Proclamation to the German nation, in Berlin on 1 February 1933. The intention was to see whether a political speech has typical common elements, or whether more extreme National Socialist (Nazi) proclamations have a different structure and emotional tenor. A further caveat is that the analysis is undertaken on an English translation of Hitler's 1933 proclamation, and not on the original German version.

It must be borne in mind that the economic circumstances in Germany in 1933 were markedly different from those in the USA in recent years. The German economy experienced the effects of the Great Depression, with unemployment soaring around the Wall Street Crash of 1929. When Adolf Hitler became Chancellor in 1933, he introduced policies aimed at improving the economy, including privatisation of state industries. National Socialist (or Nazi) Germany increased its military spending faster than any other state in peacetime, and the military eventually came to represent the majority of the German economy by the 1940s.

Figure 2 presents a word cloud analysis of both President Obama's last SOU plus Hitler's 1933 Berlin proclamation. The word cloud for President Obama's last SOU, shown in Figure 2A, displays that "will", "American", and "year" received the greatest emphases in terms of their frequency of use. These words were closely followed by "work", "America", "now", "change", "people", and "just". Further prominent words include "world", "want", "job", "can" and "need".



(**A**)



(**B**)

Figure 2. Word Cloud Analysis of President Obama's last SOU and Hitlers 1933 Berlin Proclamation: (**A**) President Obama's last SOU; and (**B**) Hitler's 1933 Proclamation.

Hitler's 1933 proclamation, as represented by the word cloud depicted in Figure 2B, reveals that the most frequently occurring word is "nation", followed by "German", "year", "will", "govern", "people", "work", 'class", "must", "world", "fourteen", "life", "upon", and so on.

Figure 3 provides bar plots of the words used most frequently in President Trump's two SOUs. The bar charts reinforce the word cloud analysis, but provide an indication of the relative frequency of use of the twenty most frequently occurring words. Figure 3A shows that, in the first SOU, "American" occurs over 50 times, followed by various indications of dollar amounts, “will” occurs more than thirty times, while “great”, “last”, “together” and “tax” occur around twenty times each.

In Trump’s second SOU, depicted by the bar chart in Figure 3B, “will” becomes the most frequently occurring word, followed by “years”, “one” and “American”, but the top few words are less frequent in President Trump’s second SOU than in his first. “American” is now the fourth most frequent word rather than the first, as in the previous SOU. Perhaps surprisingly, given the political battles enveloping the topic, “border” is the twentieth most frequently used word.

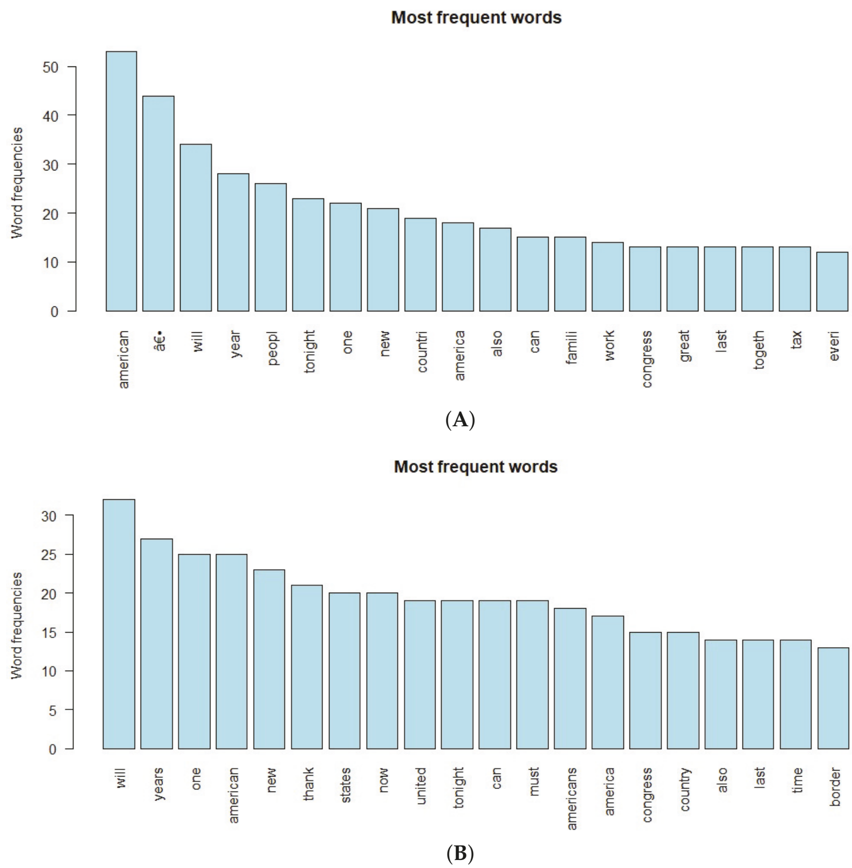
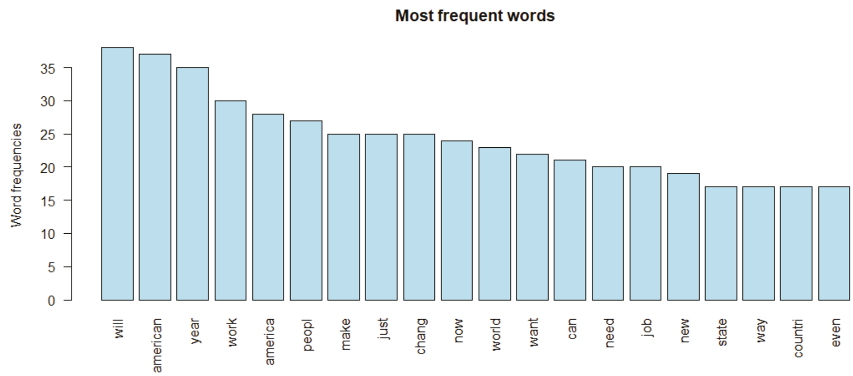
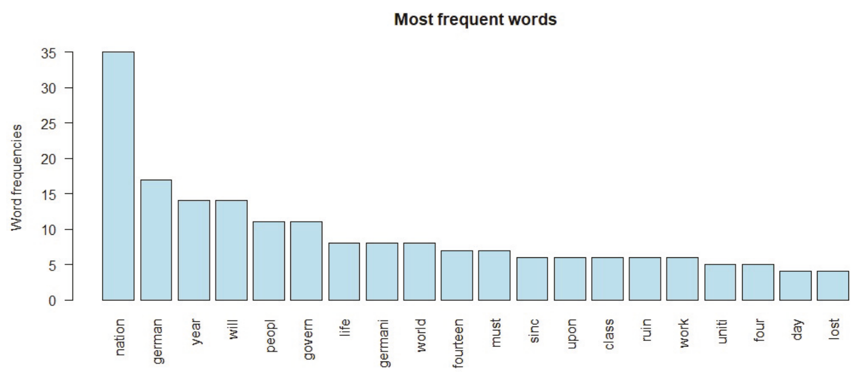


Figure 3. Bar Plots of words used frequently in President Trump’s two SOUs: (**A**) President Trump SOU1; and (**B**) President Trump SOU2.

Figure 4 provides a similar analysis for President Obama’s last SOU and for Hitler’s 1933 Proclamation. Figure 4A reveals that the most frequently used word in President Obama’s last SOU was “will”, which occurred 38 times, closely followed by “American” 37 times, and “year” 35 times. “Work”, “America” and “people” were the next most frequently occurring words.



(**A**)



(**B**)

Figure 4. Bar Plots of most frequently used words in President Obama's last SOU and in Hitler's 1933 Proclamation: (**A**) President Obama's last SOU; and (**B**) Hitler's 1933 Proclamation.

Hitler's 1933 Proclamation was a much shorter speech than the SOUs just considered. However, it was relatively dominated by the word "nation", which occurred 35 times, while the next most frequently used word was "German", mentioned 17 times, while "year" and "will" occurred 14 times each.

Patriotism and nationalism appear to be frequently occurring themes in these four very different political addresses. "American" is the first and fourth most frequently occurring words in President Trump's two SOUs, and it is the second most frequently used word in President Obama's last SOU. The most frequently used word in Hitler's 1933 Proclamation was "Nation", which had double the frequency of any other words mentioned, followed by "German". There is clearly a strong nationalistic tone in his 1933 address.

The other recurrent theme in these four political speeches is the importance of intention, as captured by the use of the word "will". It is the third and first most frequently occurring word used in President Trump's two SOUs, respectively. It is the most frequent word in President Obama's last SOU and the fourth most frequently occurring word in Hitler's 1933 Proclamation.

Table 1 shows the words most highly correlated with President Trump's frequently used words in his two SOUs. "American" is the most frequently used word in his first SOU. Its use is most highly correlated with: "bridge", "gleam", "grit", "heritage", "highway", "railway", "reclaim", "waterway", "background", "color", "creed", "dreamer", "official", "religion", and "sacred".

Table 1. Words highly correlated with frequently used words in President Trump's SOUs.

Trump SOU2018			Trump SOU2019		
Word	**Correlated Words**	**Correlation**	**Word**	**Correlated Words**	**Correlation**
American	bridge	0.34	Will	never	0.49
	gleam	0.34		Afghan	0.41
	grit	0.34		constructive	0.41
	heritage	0.34		counter terrorism	0.41
	highway	0.34		focus	0.41
	railway	0.34		groups	0.41
	reclaim	0.34		indeed	0.41
	waterway	0.34		taliban	0.41
	background	0.34		talks	0.41
	color	0.34		troop	0.41
	creed	0.34		agreement	0.38
	dreamer	0.34		achieve	0.37
	official	0.34		make	0.37
	religion	0.34		progress	0.37
	sacred	0.34		proudly	0.37
	dream	0.33		dream	0.37
	hand	0.33		holding	0.37
	land	0.31		whether	0.35
	duty	0.31		incredible	0.32
	right	0.31	American	back	0.51
	arsenal	0.44		soldiers	0.40
will	deter	0.44		astronauts	0.37
	magic	0.44		Buzz	0.37
	part	0.44		space	0.37
	someday	0.44		intellectual	0.37
	unfortunate	0.44		property	0.37
	use	0.44		Dachau	0.37
	weapon	0.44		second	0.37
	yet	0.44			
	aggression	0.40			
	moment	0.32			
	modern	0.32			

A second frequently used word is "will", which is highly correlated with "deter", 'magic", "part", "someday", "unfortunate", "use", "weapon", and "yet". The same two words are reversed in relative frequency of use in the second SOU. "Will" is most highly correlated with "never", followed by "Afghan", "constructive", "counter-terrorism", "focus", "groups", "indeed", "Taliban", "talks", and "troop". "American is most highly correlated with "back" and "soldiers".

The analysis is concerned with an examination of the extent to which political speeches by different political leaders differ. We would expect to see similarities in the two speeches by President

Trump. This includes similarities in the usage of words and correlations between pairs of words when they are made by the same politician.

Table 2 provides an analysis of the words most highly correlated with frequently used words in President Obama's last SOU and Hitler's 1933 Proclamation. The analysis of President Obama's last SOU reveals the weaknesses of a statistical analysis of individual words used as components of a particular address. The words most correlated with the word "American" were individual dollar amounts. "Will" is highly correlated with "preserve", "status-quo", and "planet".

Table 2. Words highly correlated with frequently used words in President Obama's last SOU and Hitler's 1933 Proclamation.

Obama SOU			Hitler 1933		
Word	**Correlated Words**	**Correlation**	**Word**	**Correlated Words**	**Correlation**
American	various numbers	n.a.		life	0.42
will	preserve status-quo planet	0.44 0.44 0.30	Nation	will govern regard	0.40 0.37 0.32
America	George Washington Carver Katherine Johnson Sally Ride unit	0.36 0.36 0.36 0.35	will	health lead nation back	0.50 0.40 0.40 0.33
			German	assist work rescue support	0.33 0.34 0.32 0.32

"America" is highly correlated with individual names, the components of which the program picked up individually, and it was not until the authors analysed the original text that the analysis made sense. In the speech, President Obama stated: "Now, that spirit of discovery is in our DNA. America is Thomas Edison and the Wright Brothers and George Washington Carver. America is Grace Hopper and Katherine Johnson and Sally Ride. America is every immigrant and entrepreneur from Boston to Austin to Silicon Valley racing to shape a better future".

The analysis of Hitler's 1933 Berlin Proclamation was more revealing. "Nation", the most frequently used word, is highly correlated with "life", "will", "govern", and "regard". "Will" is highly correlated with "health", "lead", "nation", "back", and "assist". Finally, "German" is highly correlated with "work", "rescue", and "support". This supports the national rebuilding of the German economy and the promotion of employment that was part of Hitler's agenda in the early 1930s. He adopted the view that the natural unit of mankind was the Volk ("the people"), of which the German people was the greatest. He also believed that the state existed to serve the Volk. This leads to a consideration of "National Socialism" (or "Nazism").

Smith ([28], pp. 18–19) suggested that "...nationalists have a vital role to play in the construction of nations, not as culinary artists or social engineers, but as political archaeologists rediscovering and reinterpreting the communal past in order to regenerate the community. Their task is indeed selective—they forget as well as remember the past—but to succeed in their task they must meet certain criteria. Their interpretations must be consonant not only with the ideological demands of nationalism, but also with the scientific evidence, popular resonance and patterning of particular ethnohistories".

Nationalism holds that each nation should govern itself, free from outside interference (self-determination), and that the nation is the only rightful source of political power (popular sovereignty). It usually involves the maintenance of a single national identity, which would be based on shared social characteristics, such as shared history culture, language, religion, and politics. President Trump, with his slogan "MAGA" (make America great again), espouses a form of Nationalism.

President Obama's last SOU is not free of nationalistic sentiment. He stated that: "I told you earlier all the talk of America's economic decline is political hot air. Well, so is all the rhetoric you hear about our enemies getting stronger and America getting weaker. Let me tell you something. The United States of America is the most powerful nation on Earth, period. Period. It is not even close. It is not even close. We spend more on our military than the next eight nations combined."

However, as the mechanical and statistical form of textmining used in this paper, though revealing, is not suited to teasing out the nuances in meaning of different forms of nationalism, emphasis is placed on a statistical analysis of the text.

We also used the R package "syuzhet" to examine the the sentiment of each string of words or sentences. We calculated the overall score and the mean or average sentiment score. The results vary slightly, depending on which lexicon or base dictionary is used. Syuzhet incorporates four sentiment lexicons. The default "syuzhet" lexicon was developed in the University of Nebraska Literary Lab under the direction of Jockers [5], the creator of the R syuzhet package. This is the default lexicon. We also cross-checked using the nrc lexicon developed by Mohammad, who is a research scientist at the National Research Council Canada (NRC) (see: http://saifmohammad.com). However, the results were quantitatively similar, and hence are not reported in the paper.

The analysis tells us whether the speech has a predominantly positive or negative score in emotional tenor. In the case of President Trumps first SOU, the total score was 113.75 and the mean score was 0.02196. This positive sentiment score is consistent with Allen, McAleer and Reid [3], who reported similarly positive results for President Trump's first SOU, on the basis of an application of the R package "sentiment", which used a different lexicography. In the previous analysis, on the basis of a primary binary division into positive and negative sentiments, 60 per cent of the first SOU, in cases where sentiment could be ascribed, was recorded as being positive.

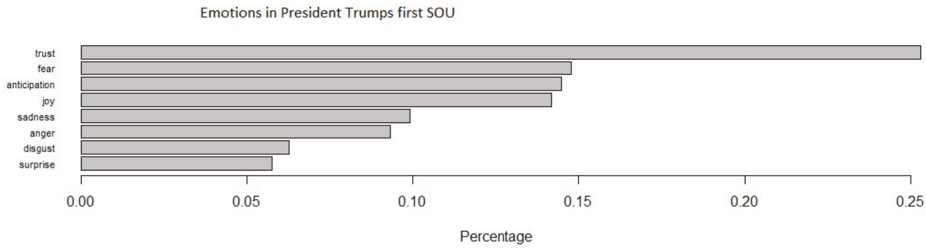
In his second SOU in 2019, the address had a total score of 139.85 and a mean score of 0.02557. His first SOU contained 5190 words and 30,271 characters, while his second SOU was slightly larger at 5442 words and 32,045 characters. President Obama's last SOU had a total score of 169.8 and a mean score of 0.02712. President Obama's last SOU was quite a large speech, containing 6233 words and 34,634 characters. In the case of Hitler's 1933 Proclamation, the sum is 8.4 and the mean is 0.0053, but Hitler's parsimonious proclamation only contained 1578 words and 9286 characters.

An interesting feature of these various speeches is the degree to which they contained predominantly positive or negative emotions. These are plotted in Figures 5 and 6. In both of President Trump's SOUs, "Trust" is the predominant emotion displayed. In all speeches, apart from President Trump's second SOU, it accounts for more than 25 per cent of the total emotional content. This is also the case in President Obama's last SOU, and in Hitler's 1933 Proclamation. In all four speeches, "Trust" dominates by a large margin in the order of 10 per cent, though it is slightly lower in President Trump's second SOU.

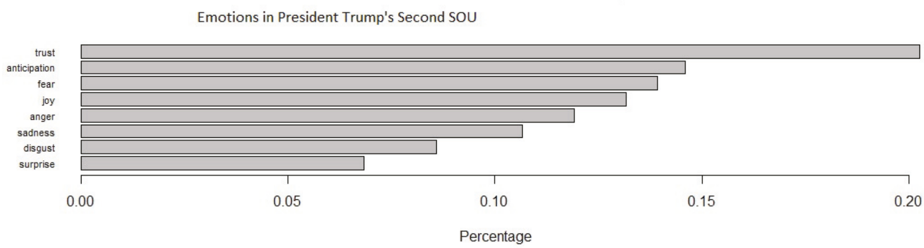
"Fear" is the second dominant emotion in Trump's SOU, and drops to third in his second SOU. "Fear" is the third emotion in President Obama's last SOU, accounting for about 14 per cent of the emotional content, but it is more prominent in Hitler's 1933 proclamation, in which it is the second ranked emotion, and accounts for about 18 per cent of the emotional content.

"Anticipation" plays a large role in President Trump's and Obama's addresses, in which it always accounts for around 15 per cent of the total emotional content; indeed, it is slightly more than 15 per cent in the case of President Obama. It is much less prominent in Hitler's Proclamation, where it is the fifth most frequently occurring emotion, accounting for about 12 per cent of the total emotional content. Indeed, a feature of Hitler's address is the predominance of negative emotions, with "fear", "sadness" and "anger" taking precedence after "trust".

In contrast, "anticipation" and "joy" are much more predominant in the two US President's SOUs, never dropping below 13 per cent in emotional content, and always ranking in the top four emotions. In Hitler's speech, "anticipation" is the fifth ranked emotion.

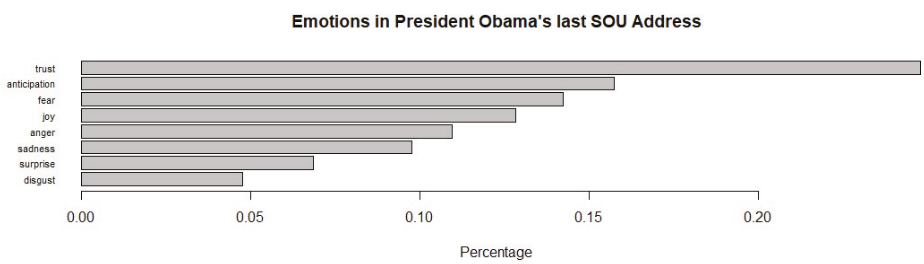


(**A**)

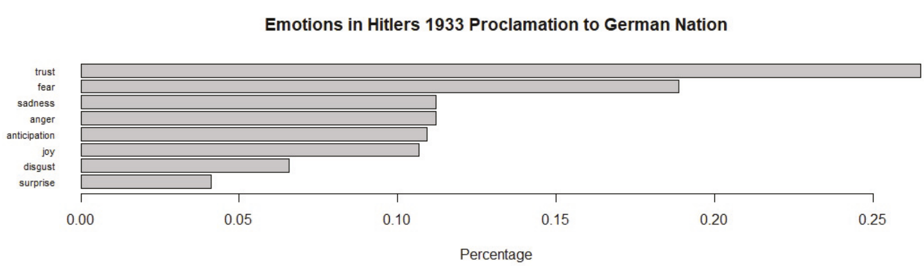


(**B**)

Figure 5. The Emotional Tenor of President Trumps two SOUs: (**A**) President Trump's First SOU; and (**B**) President Trump's Second SOU.



(**A**)

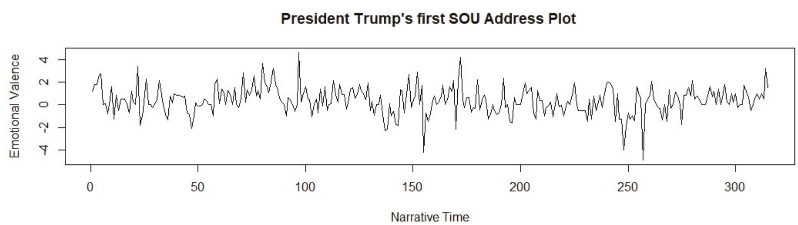


(**B**)

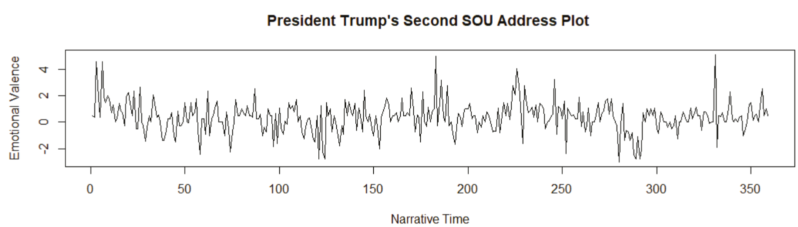
Figure 6. The Emotional Tenor of President Obama's last SOU and Hitler's 1933 Berlin Proclamation: (**A**) President Obama's last SOU; and (**B**) Hitler's 1933 Proclamation.

Another interesting feature of the four speeches is their "emotional valence", or the pattern of sequential positive and negative emotions displayed as the speech unfolds through time. Plots of these patterns are shown in Figures 7 and 8. There is a distinct change in pattern in the emotional valence of President Trump's two SOUs, as shown in Figure 7A,B. In the first, he commences on a positive emotional tone and is fairly upbeat in the first part of the speech, but then has multiple negative drops in the second half of the speech, before ending on a positive emotional note. In his second SOU, the pattern is roughly reversed, and there are more emotional negative points in the first half of the SOU, whereas the emotional volatility increases in the second half of the speech, with more frequent extreme highs and lows, and a predominantly positive tone at the end of the speech.

Figure 8A reveals that President Obama, in his last SOU, commences on a predominantly positive note, with some pronounced positive spikes, becomes more measured and negative in the middle of the speech, and ends on a predominantly positive note, with multiple positive peaks towards the end of his speech. Figure 8B shows that Hitler's much shorter 1933 Proclamation is quite volatile in the first part of the speech, becomes more measured in the second half, with fewer extreme peaks and troughs, and finishes on a positive note.

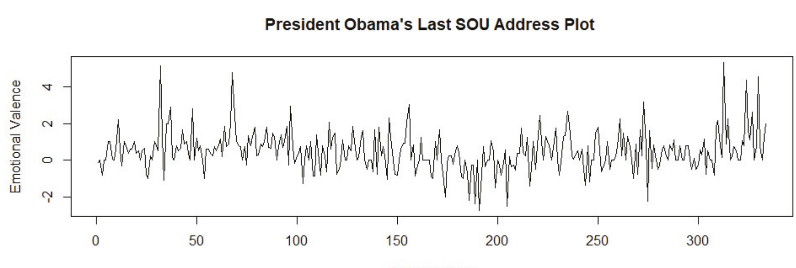


(**A**)



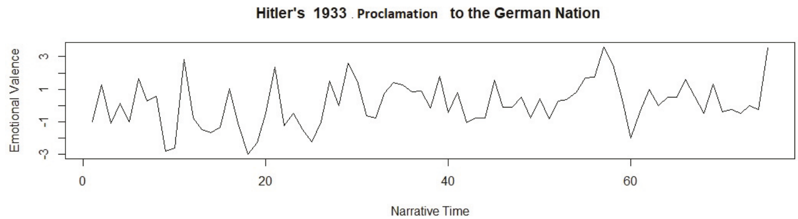
(**B**)

Figure 7. The Emotional Valence of President Trumps two SOUs: (**A**) President Trump's first SOU; and (**B**) President Trump's second SOU.



(**A**)

Figure 8. *Cont.*



(**B**)

Figure 8. The Emotional Valence of President Obama's last SOU and Hitler's 1933 Berlin Proclamation: (**A**) President Obama's last SOU; and (**B**) Hitler's 1933 Berlin Proclamation.

3.2. Zipf Mandelbrot Analysis

Zipf [22] suggested that his "Theory of Relative Frequency" is a statistical law which falls within the laws of probability. Zipf's law is an experimental law which is often applied to the study of the frequency of words in a corpus of natural language utterances. The law suggests that the frequency of any word is inversely proportional to its rank in the frequency table. In the case of the English language, the two most common words are "the" and "of", and Zipf's law states that "the" is twice as common as "of".

Figure 9 shows plots of the application of Zipf's law to the four speeches considered. The scales are in natural logarithms on both axes. A theoretical application of Zipf's law would show a slope of negative one in the plots in Figure 9, running from top left to bottom right. All plots deviate from this concept, but the greatest deviation, from the theoretical concept, is in Hitler's 1933 address, which is the most concave.

A flatter Zipf slope can indicate a more random signal, but it can also indicate a broader vocabulary that conveys a more precisely worded message. Zipf suggests that attempts to remove ambiguities should produce a flatter slope that favours the recipient. Mandelbrot [23] suggested that human languages have a slope of around 1. These political speeches are framed to favour the recipient. Hitler's is the most extreme, but this is in translation. Obama's is the closest to normal language, but is still some distance from it.

To further explore the degree of deviation in the context of these four speeches, we ran Ordinary Least Squares regressions of the log of rank regressed on the log of frequency. The results of these regressions are shown in Table 3.

The regression results in Table 3 reveal that all four regressions have F-Statistics that are highly significant, and Adjusted-R squares of 0.94, 0.94, 0.94, and 0.91, in the cases of President Trump's two speeches, President Obama's speech, and Hitler's speech, respectively. The values of the slope coefficients, all of which are significant at the one per cent level, are Trump SOUA1 slope -0.67, Trump SOUA2 slope -0.71, Obama last SOUA slope -0.74, and Hitler 1933 slope -0.57.

These results suggest that all four political speeches are framed to favour the recipient. Hitler's is the most extreme, but this is in translation. Obama's is the closest to normal language but is still some distance from it. The most simplified and audience targeted is Hitler's 1933 speech. Trump and Obama are close together, with Trump's SOUAs showing slightly greater audience targeting.

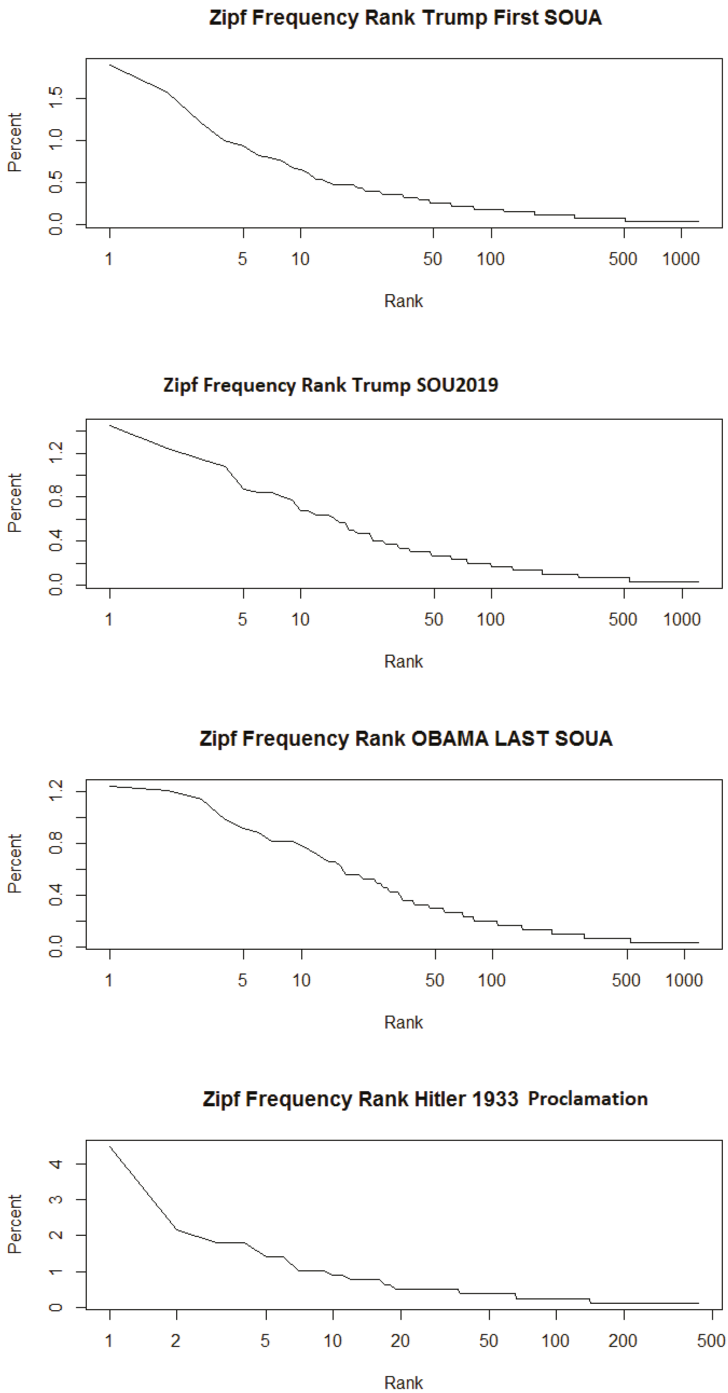


Figure 9. Zipf Plots.

Table 3. OLS, using Observations 1–1233 Dependent variable: l_freqT1.

Coefficient		**Std. Error**	***t*-Ratio**	***p*-Value**
const	4.60818	0.0301961	152.6	0.0000
l_RankT1	−0.674643	0.00487040	−138.5	0.0000
Mean dependent var	0.478800	S.D. dependent var		0.687286
Sum squared resid	35.08483	S.E. of regression		0.168823
R^2	0.939712	Adjusted R^2		0.939663
$F(1, 1231)$	19187.55	P-value(F)		0.000000
Log-likelihood	444.8414	Akaike criterion		−885.6829
Schwarz criterion	−875.4484	Hannan–Quinn		−881.8328
OLS, using Observations 1–1227 Dependent variable: l_freqT2				
Coefficient		**Std. Error**	***t*-Ratio**	***p*-value**
const	4.83631	0.0306320	157.9	0.0000
l_RankT2	−0.706661	0.00494454	−142.9	0.0000
Mean dependent var	0.514392	S.D. dependent var		0.718456
Sum squared resid	35.80636	S.E. of regression		0.170967
R^2	0.943419	Adjusted R^2		0.943373
$F(1, 1225)$	20425.42	P-value(F)		0.000000
Log-likelihood	427.1954	Akaike criterion		−850.3908
Schwarz criterion	−840.1661	Hannan–Quinn		−846.5434
OLS, using Observations 1–433 Dependent variable: l_freqH1				
Coefficient		**Std. Error**	***t*- Ratio**	***p*-Value**
const	3.21372	0.0434618	73.94	0.0000
l_RankH	−0.565233	0.00840317	−67.26	0.0000
Mean dependent var	0.342408	S.D. dependent var		0.575778
Sum squared resid	12.45621	S.E. of regression		0.170002
R^2	0.913026	Adjusted R^2		0.912824
$F(1, 431)$	4524.478	P-value(F)		1.1e–230
Log-likelihood	153.8538	Akaike criterion		−303.7076
Schwarz criterion	−295.5661	Hannan–Quinn		−300.4936
OLS, using Observations 1–1189 Dependent variable: l_freqO				
Coefficient		**Std. Error**	***t*-Ratio**	***p*-value**
const	5.05132	0.0326043	154.9	0.0000
l_RankO	−0.740851	0.00528936	−140.1	0.0000
Mean dependent var	0.543524	S.D. dependent var		0.753179
Sum squared resid	38.44997	S.E. of regression		0.179979
R^2	0.942946	Adjusted R^2		0.942898
$F(1, 1187)$	19618.01	P-value(F)		0.000000
Log-likelihood	352.9148	Akaike criterion		−701.8296
Schwarz criterion	−691.6679	Hannan–Quinn		−698.0000

4. Conclusions

In this paper, we have analysed President Trump's two SOUs and contrasted the content with those of the last SOU of President Obama and that of Hitler's 1933 Berlin Proclamation. All four are political speeches, and share a great deal of commonality. The sentiment analysis showed that they emphasize the nation, America and American, in the case of the two US Presidents, and Nation and German, in the case of Hitler. The word "will" features prominently in all four speeches, and relates to the respective political agendas of the speakers. The emotional tenor of the speeches of the two US Presidents is more positive than adopted by Hitler in his 1933 Berlin Proclamation. All speakers chose to end their speeches on a positive emotional note, and all four speeches contain Nationalistic elements.

The analysis also includes an application of the Zipf and Mandelbrot laws. The fact that all four had a slope of less then negative one, which would be standard speech in this framework, indicates that all three speakers had targeted their audiences and simplified the language used in their speeches. Hitler's use of language was the most distant from standard speech with a score of negative 0.57. This suggests his status as a skillful mob-orator is justified. Presidents Trump and Obama were less extreme but still had slope coefficients with values around negative 0.7, suggesting that they also target their audiences carefully.

The limitation of the text-mining approach adopted in the analysis of the contents of these four speeches is that it does not feature a verification of the statements made, and cannot pick up nuances in meaning and context. However, the approach does provide a broad indication of the structure and emotional flavour of the content, subject to the limitations of the lexicon applied. The Zipf analysis highlights the degree to which speech patterns within the speeches deviate from normal language values.

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sustainability

Article

A Sustainability-Oriented Enhanced Indexation Model with Regime Switching and Cardinality Constraint

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Abstract: Enhanced indexation is an active portfolio management strategy aimed to find a portfolio outperforming a market index. To ensure stable returns and to avoid extreme losses, a sensible enhanced indexation model should be sustainable, where the parameters of the model should be adjusted adaptively according to the market environment. Hence, in this paper, we propose a novel sustainable regime-based cardinality constrained enhanced indexation (RCEI) model, where different benchmarks and cardinalities can be imposed under different market regimes. By using historical observations, the RCEI model is transformed into a deterministic optimization problem with an ℓ_0 norm constraint. We design a partial penalty method coupled with the proximal alternating direction method of multipliers (ADMM) to solve the deterministic optimization problem. Numerical results in UK and US financial markets confirm the superb performance of the sustainability-oriented RCEI model and the efficiency of the algorithm.

Keywords: enhanced indexation; regime switching; cardinality constraint; proximal ADMM

1. Introduction

As the global financial market is riddled with more and more uncertainty, there is a growing awareness of incorporating sustainability-relates insights into investment analysis and management; therefore, investors boost their chances for long-term and sustainable success. Incorporating sustainability insights can provide a more holistic view of the risks and opportunities associated with a given investment. In response to the increasing interest, there is a strong need to develop sustainable investing approaches and products.

The research on financial sustainability is in its infancy as only a handful of articles briefly touched on it [1–6]. Nurmakhanova et al. [3] claimed that a sustainable microfinance institution is the one that operates profitably and does not require subsidies to succeed. By integrating a composite sustainability index of a project into Markowitz mean-variance model, Dobrovolskienė and Tamošiūnienė [4] presented a sustainability-oriented model of financial resource allocation in a project portfolio. Li et al. [5] studied the Maslow portfolio selection model to meet the need of individuals with low financial sustainability who prefer to satisfy their lower-level needs first, and then look for higher-level needs. Nevertheless, the study of financial sustainability in portfolio management, especially in the enhanced indexation area, is far from adequate.

Financial portfolio management has long been of keen interest to fund managers, individual investors, and scholars. Relentless efforts have been made to quantify market dynamics and turn them into more strategic and sustainable investment tools. Enhanced indexation is an active portfolio management strategy, which is proposed to find a portfolio outperforming a market index [7–21].

Due to the existence of market frictions such as transaction costs and management expenses, the number of invested assets in the tracking portfolio should be limited. Nevertheless, finding a global optimal portfolio of a cardinality constrained optimization problem is generally NP-hard [22]. Therefore, some scholars investigated the enhanced indexation problems in the aspects of modeling and solution methods. Riepe and Werner [7] first studied the enhanced indexation problem and it became a fertile area of research. Dose and Cincotti [9] sought a relatively high excess return within a reduced tracking error by adopting the historical look-back approach. They solved the problem in a two-step heuristic method, while this method could not ensure the global optimality of the obtained portfolios. Canakgoz and Beasley [11] presented mixed-integer linear programs (MILP) for the enhanced indexation problem from the regression viewpoint. They adopted a two-stage approach to find the optimal solution, in which each stage can be solved by Cplex solver. Lejeune [13] formulated a stochastic enhanced indexation model whose goal is to maximize the excess return that can be attained, while ensuring that the semi-deviation risk does not exceed a specified limit. He provided the game theoretical framework when the distribution of the random return is known to belong to the ellipsoidal distribution family. Guastaroba and Speranza [15] illustrated mixed-integer linear programming models for index tracking and enhanced indexation, in which the enhanced indexation model was to maximize the over-performance with respect to the market index, while ensuring that the tracking error would not exceed a given threshold. In addition, the MILP is solved by a heuristic framework called kernel search. Roman et al. [16] studied the enhanced indexation problem based on a second-order stochastic dominance model. They adopted the cutting plane method to arrive at the optimal solution for the problem, whereas the number of selected stocks could not be restricted strictly due to the absence of a cardinality constraint. Xu et al. [19] showed a sparse enhanced indexation model with cardinality and chance constraints in the distributionally robust framework. The Fama–French three-factor model is used to reformulate the robust chance constraint of random variables. They applied a hybrid genetic algorithm to solve the NP-hard problem.

Nevertheless, all of these conventional enhanced indexation models referred to above—missing sustainability in scope—failed in capturing intrinsically dynamic market environments and thus only provided partial pictures. In particular, sustainability in enhanced indexation problem is a fundamental issue to ensure stable returns and to avoid extreme losses in a long-term investment process. In the scope of solution methods, the existing algorithms still have many defects. Even though some mixed integer programming [11,17] can be solved by standard software programs, which are not applicable in large-scale problems due to the curse of dimensionality. In addition, hybrid heuristic methods [8,15,19,20] based on genetic algorithms, kernel search or simulated annealing are not able to guarantee the optimality conditions of the obtained solutions. Therefore, more work are in great demand to establish scientific sustainability models to reflect the market environment and to design efficient algorithms that can solve the large-scale cardinality constrained enhanced indexation problem.

Inspired by the enhanced indexation models of Lejeune's [13], Guastaroba and Speranza [15], in this paper, we emphasize the standpoint of financial sustainability to avoid extreme losses when pursuing higher excess profits in a long-term investment process. Unlike the ellipsoidal distribution assumption by Lejeune or the heuristic framework by Guastaroba and Speranza, our proposed stochastic enhanced indexation model is determined by the historical observations' approximation, which is a universal framework to formulate the stochastic optimization problem into the deterministic form [11,17,20]. However, there is almost no literature on how to select the historical observations from the dataset, which will directly influence the performance of the enhanced indexation model. In fact, historical sample series sometimes have obvious random-effects in the historical dependence relationship [23]. Hence, for guaranteeing the sustainability of the enhanced indexation problem, in this paper, it is necessary to consider the nonlinear relationship between the forthcoming and historical return rates. In addition, the parameters of the enhanced indexation model should be adjusted adaptively according to the market environment. This idea is consistent with the regime switching technique [24], which has the strength of not only reflecting the change of the market environment but also demonstrating the nonlinear dynamic relationship among market environments in different time periods [25,26]. Therefore, in this paper, we properly select different risk thresholds and cardinality bonds in the enhanced indexation model according to different market regimes.

To help investors capitalize on opportunities in sustainable investing in this growing turbulent global market, this paper offers insights on how to integrate variable financial market environments with the investment process—from defining the objectives and approach for an investment strategy through developing the algorithms. More specifically, we propose a sustainable regime-based cardinality constrained enhanced indexation (RCEI) model. Incorporating the switching of market regimes into our analysis, we divide the historical observations with respect to different market regimes and introduce the regime-dependent threshold and cardinality upper bound to improve the model. In addition, we adopt a splitting algorithm based on the proximal alternating direction method of multipliers (ADMM). The new enhanced indexation model and proposed algorithm are examined by numerical tests for its sustainability and efficiency in different real financial markets. The main contributions of this paper can be summarized as follows:

- On account of the growing uncertainty in financial markets, we introduce a novel sustainability-oriented enhanced indexation model with the regime switching technique to avoid the extreme losses in the long-term assets management process, with the purpose of reflecting the fluctuations of the financial market timely and obtaining the sustainable investment profits.
- Considering the significant cardinality constraint in the deterministic formulation, we adopt a partial penalty method coupled with the proximal ADMM, which can solve the resulting nonsmooth and nonconvex problem effectively and efficiently.
- We conduct numerical tests in different financial markets for long-term processes. The evidence demonstrates the scientific soundness and the sustainability of the RCEI model as well as the efficiency of the proposed hybrid algorithm.

The paper is organized as follows: in Section 2, we establish the sustainable stochastic enhanced indexation model with regime switching and cardinality constraint, and then transform the formulation by using historical observations. In Section 3, we present a partial penalty method embedded with the proximal ADMM for solving the transformed deterministic optimization problem. In Section 4, we illustrate the numerical results about the applications of the RCEI model in the FTSE 100 and S&P 500 markets. We conclude this paper in Section 5.

2. Sustainability-Oriented Enhanced Indexation Model

In classic enhanced indexation problems, the main focus is to maximize the excess return and minimize the tracking error. However, a larger excess return is in contradiction with a lower tracking error if we consider the total deviation in the optimal portfolio. Therefore, we consider a stochastic optimization model where the expected excess return is maximized at the same time controlling the lower semi-absolute tracking error and the maximum number of assets being invested. The concrete cardinality constraint enhanced indexation problem is as follows:

$$\begin{array}{ll} \max\limits_{x} & \mathbb{E}[R^\top x - R_I] \\ \text{s.t.} & \mathbb{E}[(R^\top x - R_I)_-] \le \alpha, \\ & e_N^\top x = 1, \\ & \|x\|_0 \le K, \end{array} \tag{1}$$

where $x \in \mathbb{R}^N$ is a decision vector that denotes the portfolio. R is an N-dimensional random vector that denotes the random return rates of N assets. R_I is a random variable denoting the random return rate of the market index. $\alpha \in \mathbb{R}_+$ is a given threshold to constrain the lower semi-absolute tracking error. $e_N \in \mathbb{R}^N$ is an all-one vector with length N. $\|x\|_0$ is the cardinality of x, which denotes the number of nonzero components in x. The constraint $\|x\|_0 \le K$ means that the number of non-zero entries in the optimal portfolio is not larger than K. To deal with the general case in different financial markets, we do not restrict the short-selling in this paper. We should point out that our algorithm proposed later can also be applied to the no short-selling case.

In existing enhanced indexation models referred above, the benchmark is always a fixed scale or a given market index, while, as we pointed out in the Introduction, the market environment varies significantly according to different market regimes. Hence, for guaranteeing the financial sustainability, the benchmarks in an enhanced indexation model should be properly selected according to specific market regimes. Typically, in a bull market, the investor could choose higher benchmarks; in a bear market, the investor might set lower benchmarks in the hope of avoiding the absolute loss at the same time.

Before introducing the sustainable enhanced indexation model with regime switching, we present the basic setting for the regime switching. We assume that the current regime is s_0, and the regime during the next investment period is s. We assume that the regime switching is Markovian, and there are J possible regimes: $s^1, s^2, \ldots, s^J$. $Q_{s^i s^j} := Q\{s_f = s^j : s_0 = s^i\}$ represents the transition probability from regime s^i in the current period to regime s^j in the next period. In this paper, we assume that the Markovian regime switching process is stationary. This means that, for any period, the transition probability matrix is

$$Q = \begin{bmatrix} Q_{s^1 s^1} & Q_{s^1 s^2} & \cdots & Q_{s^1 s^J} \\ Q_{s^2 s^1} & Q_{s^2 s^2} & \cdots & Q_{s^2 s^J} \\ \cdots & \cdots & \cdots & \cdots \\ Q_{s^J s^1} & Q_{s^J s^2} & \cdots & Q_{s^J s^J} \end{bmatrix}.$$

Under this setting, as an extension of the model (1), we can introduce the following sustainable regime-based cardinality constrained enhanced indexation model:

$$\text{(RCEI)} \qquad \begin{array}{ll} \max\limits_{x} & \mathbb{E}[R^\top x - R_I(s_f)] \\ \text{s.t.} & \mathbb{E}[(R^\top x - R_I(s_f))_- : s_f = s^j] \le \alpha(s^j),\ j = 1, 2, \ldots, J, \\ & e_N^\top x = 1, \\ & \|x\|_0 \le K(s_0), \end{array} \tag{2}$$

where $R_I(s_f)$ is the return rate of the market index whose distribution relies on the forthcoming market regime s_f. Meanwhile, we set the cardinality upper bound $K(s_0)$ according to the current market regime s_0. For example, in a bull market environment, investors can set a larger threshold of the lower semi-absolute tracking error and focus on fewer blue chip stocks in order to reap higher excess returns. On the contrary, in a bear market environment, investors opt for a more diverse investment strategy to secure financial sustainability. They can set a smaller threshold of the tracking error under the index to reduce the risk and avoid the absolute investment losses.

We use the historical observations for transforming the stochastic optimization problem (2). Concretely, the expectations in the problem are approximated by historical observations: we assume that there are T historical observations of R, $\{r_1, r_2, \ldots, r_T\}$, the historical observations of R_I are $\{r_I(s(1)), r_I(s(2)), \ldots, r_I(s(T))\}$, where $s(t)$, for $t = 1, 2, \ldots T$, denotes the market regime to which the t-th observation belongs.

We define the historical observations' index set as $S = \{1, 2, \ldots, T\}$, then we can divide S into J parts corresponding to the J market regimes. We denote the set of observations under the j-th market regime as S_j, then $S = \bigcup_{1,2,\ldots,J} S_j$ and $S_i \bigcap S_j = \emptyset$ for $i, j = 1, 2, \ldots, T$ and $i \neq j$. In S_j, we have T_j historical observations, and $\sum_{j=1}^{J} T_j = T$. We derive the sample reformulation of the RCEI model as:

$$\begin{array}{ll} \max\limits_{x} & \sum\limits_{j=1}^{J}\left(Q(s_0,s^j)\frac{1}{T_j}\sum\limits_{t\in S_j}(r_t^\top x - r_I(s(t)))\right) \\ \text{s.t.} & \frac{1}{T_j}\sum\limits_{t\in S_j}\left[(r_t^\top x - r_I(s(t)))_-\right] \le \alpha(s^j),\ j=1,2,\ldots,J, \\ & e_N^\top x = 1, \\ & \|x\|_0 \le K(s_0). \end{array} \tag{3}$$

We notice that the term $r_I(s(t))$ in the objective function does not affect the optimal solution of the deterministic optimization problem, therefore we can get rid of this term in the following formulations. However, the negative part function in problem (3) leads the programming to a nonlinear optimization problem. By introducing an auxiliary vector $y = (y_1; y_2; \ldots; y_T) \in \mathbb{R}^T$, problem (3) can be transformed into the following cardinality constrained linear programming problem:

$$\begin{array}{ll} \max\limits_{x,y} & \sum\limits_{j=1}^{J}\left(Q(s_0,s^j)\frac{1}{T_j}\sum\limits_{t\in S_j} r_t^\top x\right) \\ \text{s.t.} & \frac{1}{T_j}\sum\limits_{t\in S_j} y_t \le \alpha(s^j),\ j=1,2,\ldots,J, \\ & y_t \ge r_I(s(t)) - r_t^\top x,\ t=1,2,\ldots,T, \\ & y_t \ge 0,\ t=1,2,\ldots,T, \\ & e_N^\top x = 1, \\ & \|x\|_0 \le K(s_0). \end{array} \tag{4}$$

Problem (4) is very often a large-scale optimization problem with linear and cardinality constraints since the number of stocks N and observations T are large enough. Fortunately, we notice that, in this formulation, the decision variables x and y can be divided into groups. This feature reminds us that the splitting methods, such as the proximal ADMM algorithm, can be adopted for solving this large-scale optimization problem.

3. Proximal ADMM Algorithm for Solving the Enhanced Indexation Model

In this section, we adopt the proximal ADMM algorithm for solving the sustainability-oriented enhanced indexation model. ADMM was first introduced in the early 1970s [27]. The Bregman modification of ADMM was recently proposed by Zhang et al. [28]; they showed the convergence for convex objective functions under the general Bregman distance. Chen et al. [29] demonstrated that the direct extension of the classic ADMM to the multi-block minimization problem is not necessarily convergent even if the objective function is the sum of separable convex functions. Following Chen and Zhuang [30], we adopt the partial penalty method embedded with the proximal ADMM algorithm for solving the deterministic RCEI model.

To adopt the proximal ADMM method better and express the formulation simply, we combine the decision variables x and y together, and represent it as $w = (x; y) \in \mathbb{R}^{N+T}$. Therefore, $x = Aw$, $y = Bw$, where $A = (I_N, 0) \in \mathbb{R}^{N\times(N+T)}$, $B = (0, I_T) \in \mathbb{R}^{T\times(N+T)}$, and I denotes the identity matrix. Then, $y_t = B_t w$, for $t = 1, 2, \ldots, T$, where B_t is the t-th row of B, and $\sum_{t\in S_j} y_t = \sum_{t\in S_j} B_t w$. Then, problem (4) can be reformulated as:

$$\begin{array}{ll} \max\limits_{x,w} & \sum\limits_{j=1}^{J}\left(Q(s_0,s^j)\frac{1}{T_j}\sum\limits_{t\in S_j} r_t^\top Aw\right) \\ \text{s.t.} & \frac{1}{T_j}\sum_{t\in S_j} B_t w \le \alpha(s^j),\ j=1,2,\ldots,J, \\ & B_t w \ge r_I(s(t)) - r_t^\top Aw,\ t=1,2,\ldots,T, \\ & Bw \ge 0, \\ & e_N^\top Aw = 1, \\ & Aw - x = 0, \\ & \|x\|_0 \le K(s_0). \end{array} \tag{5}$$

In order to simplify the deterministic RCEI model further, we treat the cardinality constraint individually and combine the other constraints of the same type together. Specifically, define the cardinality set $\mathcal{C}_{s_0} := \{x \in \mathbb{R}^N : \|x\|_0 \leq K(s_0)\}$, and let $\delta_{\mathcal{C}_{s_0}}(x)$ denote the indicator function of x with respect to $\mathcal{C}_{s_0}$, i.e., $\delta_{\mathcal{C}_{s_0}}(x) = 0$ if $\|x\|_0 \leq K(s_0)$, and $\delta_{\mathcal{C}_{s_0}}(x) = \infty$, otherwise. We should point out that $\delta_{\mathcal{C}_{s_0}}(x)$ can be abbreviated as $\delta_{\mathcal{C}}(x)$ as long as it will not cause any ambiguity. Let $A_1 = (A_1^1; A_1^2; \ldots; A_1^J) \in \mathbb{R}^{J\times(N+T)}$, where $A_1^j = \frac{1}{T_j}\sum_{t\in S_j} B_t \in \mathbb{R}^{1\times(N+T)}$ for $j = 1, \ldots, J$. $\bar{\alpha} = (\alpha(s^1); \alpha(s^2); \ldots; \alpha(s^J)) \in \mathbb{R}^J$. $A_2 = (A_2^1; A_2^2; \ldots; A_2^T) \in \mathbb{R}^{T\times(N+T)}$, where $A_2^t = -r_t^\top A - B_t \in \mathbb{R}^{1\times(N+T)}$ for $t = 1, \ldots, T$. $r_I = (r_I(s(1)); r_I(s(2)); \ldots; r_I(s(T))) \in \mathbb{R}^T$. $c = -(\frac{1}{T}\sum_{t=1}^T r_t^\top A)^\top \in \mathbb{R}^{N+T}$. Moreover, we joint some equality and inequality constraints together, respectively: $\bar{A} = (A_1; A_2; -B)$, $\bar{b} = (\bar{\alpha}; -r_I; 0)$, $\bar{C} = e_N^\top A$, $\bar{d} = 1$. Then, the reformulated problem (5) can be further simplified as

$$\begin{array}{ll} \min\limits_{x,w} & c^\top w + \delta_{\mathcal{C}}(x) \\ \text{s.t.} & \bar{A}w \leq \bar{b}, \\ & \bar{C}w = \bar{d}, \\ & Aw - x = 0. \end{array} \tag{6}$$

Since the direct application of ADMM in problem (6) fails to preserve its convergence property [29], we consider the partial penalty method inspired by Chen and Zhuang [30]. By introducing auxiliary vectors $u \in \mathbb{R}^{J+2T}$ and $v \in \mathbb{R}$, the partial penalty enhanced indexation subproblem can be formulated as:

$$\begin{array}{ll} \min\limits_{x,w,u,v} & c^\top w + \mu(\|u_+\|^2 + \|v\|^2) + \delta_{\mathcal{C}}(x) \\ \text{s.t.} & \bar{A}w - u = \bar{b}, \\ & \bar{C}w - v = \bar{d}, \\ & Aw - x = 0, \end{array} \tag{7}$$

where $\mu > 0$ denotes the penalty parameter of problem (6). For more concise expression of the constraints, we denote

$$\mathcal{A} = \begin{bmatrix} \bar{A} \\ \bar{C} \\ A \end{bmatrix}, \; \mathcal{B} = \begin{bmatrix} -I & 0 \\ 0 & -I \\ 0 & 0 \end{bmatrix}, \; \mathcal{D} = \begin{bmatrix} 0 \\ 0 \\ -I \end{bmatrix}, \; b = \begin{bmatrix} \bar{b} \\ \bar{d} \\ 0 \end{bmatrix}, \tag{8}$$

then the constraints in problem (7) can be merged as:

$$\mathcal{A}w + \mathcal{B}\begin{bmatrix} u \\ v \end{bmatrix} + \mathcal{D}x = b. \tag{9}$$

Then, the augmented Lagrangian function of the enhanced indexation subproblem (7) is:

$$\begin{aligned} \mathcal{L}_\mu(x, w, u, v, \lambda; \beta) = \; & c^\top w + \mu(\|u_+\|^2 + \|v\|^2) + \delta_{\mathcal{C}}(x) \\ & + \lambda^T\left(\mathcal{A}w + \mathcal{B}\begin{bmatrix} u \\ v \end{bmatrix} + \mathcal{D}x - b\right) + \frac{\beta}{2}\left\|\mathcal{A}w + \mathcal{B}\begin{bmatrix} u \\ v \end{bmatrix} + \mathcal{D}x - b\right\|^2, \end{aligned} \tag{10}$$

where λ denotes the Lagrangian multiplier of constraint (9), and $\beta > 0$ denotes the penalty parameter of the partial penalty subproblem. Then, we can adopt the partial penalty method embedded with the proximal ADMM to solve the enhanced indexation problem. The concrete algorithm can be presented in Algorithm 1.

Algorithm 1: Partial penalty proximal ADMM for enhanced indexation problem

- **Step 1.** Given an initial point $(x^0, w^0) \in \mathbb{R}^N \times \mathbb{R}^{N+T}$, the outer tolerance $\epsilon_O > 0$, $\gamma > 1$. Let $k = 1$, $\mu^k > 0$;
- **Step 2.** Solve the enhanced indexation subproblem (7) by the proximal ADMM algorithm:
  - **Step 2.1.** Given $\mu = \mu^k$, the inner tolerance $\epsilon_I > 0$, $\sigma > 0$. Let $\beta > 0$, $(x^0, w^0) = (x^{k-1}, w^{k-1})$, $u^0 = \bar{A}w^0 - \bar{b}$, $v^0 = \bar{C}w^0 - \bar{d}$, $\lambda^0 \in \mathbb{R}^{J+2T+N+1}$, $i = 0$;
  - **Step 2.2.** Perform the $(i+1)$-th iteration as follows:

$$\left\{\begin{array}{lcl} x^{i+1} & = & \arg\min\limits_{x} \mathcal{L}_\mu(x, w^i, u^i, v^i, \lambda^i; \beta), \\ w^{i+1} & = & \arg\min\limits_{w} \{\mathcal{L}_\mu(x^{i+1}, w, u^i, v^i, \lambda^i; \beta) + \frac{\sigma}{2}\|w - w^i\|^2\}, \\ \begin{bmatrix} u^{i+1} \\ v^{i+1} \end{bmatrix} & = & \arg\min\limits_{u,v} \mathcal{L}_\mu(x^{i+1}, w^{i+1}, u, v, \lambda^i; \beta), \\ \lambda^{i+1} & = & \lambda^i + \beta(\mathcal{A}w^{i+1} + \mathcal{B}\begin{bmatrix} u^{i+1} \\ v^{i+1} \end{bmatrix} + \mathcal{D}z^{i+1} - b), \end{array}\right.$$

  - **Step 2.3.** If the inner stopping criterion

$$\max\{\mu, \beta, 1\}(\|w^{i+1} - w^i\| + \|(\lambda^{i+1} - \lambda^i)/\beta\|) \le \epsilon_I$$

    is satisfied, stop the proximal ADMM algorithm and go to Step 3; otherwise, let $\beta = \gamma\beta$, $i = i + 1$ and go to Step 2.2;
- **Step 3.** If the outer stopping criterion

$$\|\mathcal{A}w^k + \mathcal{B}\begin{bmatrix} u^k \\ v^k \end{bmatrix} + \mathcal{D}x^k - b\| \le \epsilon_O$$

  is satisfied, stop the algorithm and return the approximate optimal solution (x^k, w^k); otherwise, let $\mu^{k+1} = \gamma\mu^k$ and go to Step 2 with $k = k + 1$.

Remark 1. *The proximal coefficient $\sigma > 0$ in Algorithm 1 controls the proximity of the new iteration point to the last one. It is obvious that the proximal regularized subproblem reduces to the classic ADMM algorithm if we set $\sigma = 0$.*

Remark 2. *Step 2.2 in Algorithm 1 can be further represented as:*

$$\left\{\begin{array}{lcl} x^{i+1} & = & \mathrm{Proj}_C(Aw^i + \lambda_x^i/\beta), \\ w^{i+1} & = & H^{-1}\left(\sigma w^i - c - \bar{A}^\top\lambda_u^i - \bar{C}^\top\lambda_v^i - A^\top\lambda_x^i + \beta\bar{A}^\top(u^i + \bar{b}) + \beta\bar{C}^\top(v^i + \bar{d}) + \beta A^\top x^{i+1}\right), \\ u^{i+1} & = & \mathrm{Prox}^{\beta}_{\mu\|(\cdot)_+\|^2}(\bar{A}w^{i+1} - \bar{b} + \lambda_u^i/\beta), \\ v^{i+1} & = & \mathrm{Prox}^{\beta}_{\mu\|\cdot\|^2}(\bar{C}w^{i+1} - \bar{d} + \lambda_v^i/\beta), \\ \lambda^{i+1} & = & \lambda^i + \beta(\mathcal{A}w^{i+1} + \mathcal{B}\begin{bmatrix} u^{i+1} \\ v^{i+1} \end{bmatrix} + \mathcal{D}x^{i+1} - b), \end{array}\right.$$

where $\lambda = (\lambda_u; \lambda_v; \lambda_x) \in \mathbb{R}^{(J+2T)\times 1\times N}$, $H = \beta\mathcal{A}^\top\mathcal{A} + \sigma I$. Given $z \in \mathbb{R}^N$ and $\rho > 0$, the proximal mapping of f with respect to z is defined as:

$$\mathrm{Prox}_f^\rho(z) := \arg\min_s\{f(s) + (\rho/2)\|s - z\|^2 : v \in \mathbb{R}^N\}.$$

It is known that the proximal operator $\mathrm{Prox}_{\delta_C}(\cdot)$ can be reduced to the projection operator $\mathrm{Proj}_C(\cdot)$, as shown in the update step for x^{i+1}. Both proximal and projection operators have their closed form expressions in our proposed *problem, which means that each step in Algorithm 1 has their closed form, and, therefore, the computation time can be guaranteed to some extent.*

Remark 3. *The convergence of Algorithm 1 is ensured by the theoretical analysis in the work of Chen and Zhuang [30].*

4. Empirical Results

In this section, we carry out empirical tests to examine performances of the sustainability-oriented RCEI model in different financial markets. All formulations derived from enhanced indexation problems are solved by Algorithm 1 proposed in Section 3.

4.1. Data Sets and Model Settings

We consider two typical indices and different data sets correspondingly with different scales: the FTSE 100 index and the S&P 500 index, for testing the proposed RCEI model. These two indices represent the different financial markets in UK and US. The investment stocks are the corresponding components in the two indices: 100 stocks constituting the FTSE 100 index and 500 stocks constituting the S&P 500 index. All data are selected as the adjusted closing prices of stocks in every week: the FTSE 100 index data set is from 1 January 2004 to 27 December 2018; the S&P 500 index data set is from 1 January 2007 to 31 December 2018, which are used for computing each index's and stock's logarithmic weekly return rates. The original data are downloaded from Yahoo finance (http://finance.yahoo.com). We partition each data set into two subsets: a training data set and a testing data set. The training data set, also called the in-sample set, is used to determine the optimal enhanced indexation portfolio. The testing data set, also called the out-of-sample set, consists of the rest of the data and is used to test the performance of the resulting optimal portfolio. We adopt a rolling forward framework. For each week in the out-of-sample period, we find the optimal portfolio from the RCEI model with the historical data in the last 50 weeks before the week. This provides us 732 out-of-sample optimal portfolios, one per week, to track the FTSE 100 index, and 576 out-of-sample optimal portfolios to track the S&P 500 index. With the market price data in out-of-sample periods, we compute the return rates of these out-of-sample portfolios. All numerical tests are carried out with Matlab 9.2.0 (2017a) (MathWorks, Natick, MA, United States). Table 1 summarizes the settings of the tests.

Table 1. Test settings.

	Constituent Stocks	Benchmark	K	In-Sample Weeks	Out-of-Sample Period (Weeks)
Test 1	100	FTSE 100	5, 10, 20	50	2004.12.23–2018.12.27 (732)
Test 2	500	S&P 500	5, 10, 20	50	2007.12.24–2018.12.31 (576)

As common practice, we assume that there exist three market regimes: the bull regime, denoted as s^1, means that the market is going up; the consolidation regime, denoted as s^2, indicates that the market is in the transitional period between recovery and recession; and the bear regime, denoted as s^3, means that the market is going down. We use the method adopted in Liu and Chen [31] to determine market regimes based on the average values of the market index over a time window. By using the in-sample data, we estimate the transition probability matrices for the FTSE 100 and S&P 500 indices, respectively:

$$Q_{\mathrm{FTSE}} = \begin{bmatrix} 0.9023 & 0.0951 & 0.0026 \\ 0.2482 & 0.5674 & 0.1844 \\ 0.0237 & 0.1361 & 0.8402 \end{bmatrix}, \quad Q_{\mathrm{S\&P}} = \begin{bmatrix} 0.9342 & 0.0608 & 0.0051 \\ 0.2933 & 0.5467 & 0.1600 \\ 0.0310 & 0.0775 & 0.8915 \end{bmatrix}.$$

From the diagonal elements in Q_{FTSE} and $Q_{\text{S\&P}}$, we see that both markets are stable to stay in the bull or bear regime, but there is a relatively high possibility to switch from the consolidation regime into the bull or bear regime. This scenario is consistent with the real market situation.

Table 2 gives the mean and standard deviation of each index's out-of-sample return rates under different market regimes. It reflects the difference of weekly return rates in three market regimes.

Table 2. Mean and standard deviation of out-of-sample return rates under different market regimes.

Index	Mean (s^1)	Mean (s^2)	Mean (s^3)	Mean	Std (s^1)	Std (s^2)	Std (s^3)	Std
FTSE 100	0.0036	0.0010	−0.0063	0.0005	0.0187	0.0195	0.0318	0.0224
S&P 500	0.0033	0.0014	−0.0071	0.0009	0.0190	0.0240	0.0396	0.0254

We can see from Table 2 that both the expected return rates and the standard deviations are noticeably different among three different market regimes. Under the bull regime, the expected return rates are the highest and always positive; under the bear regime, they are the lowest and always negative; and, under the consolidation regime, they are in the middle. Correspondingly, the standard deviations of two indices under the bear regime are always higher than those under the bull or consolidation regime. These phenomena capture the real market well: the investment under the bear regime is usually active, which leads to a rather low return rate with large volatility; while the investment under the bull regime is less frequent, which leads to a high return rate with a relative small volatility.

4.2. Out-of-Sample Results

In practice, the primary concern is the out-of-sample performance of the determined portfolio. Therefore, we only demonstrate the out-of-sample results here. In the RCEI model, the lower semi-absolute tracking error thresholds $\alpha(s^1), \alpha(s^2), \alpha(s^3)$ are chosen as $0.007, 0.005, 0.003$, respectively. The cardinality upper bounds are set to $K(s^1) = 5$, $K(s^2) = 10$, $K(s^3) = 20$. That is to say, in a bull market, we prefer a more concentrated investment policy while we allow a larger tolerance of the losses under the index. In a bear market, we prefer a more diversified investment policy and set a smaller tolerance of the losses under the index, to reduce the risk. To elaborate whether the regime switching technique can improve the stability in enhanced indexation problems, we also test the cardinality constrained enhanced indexation model without regime switching, denoted by the CEI model for reference. We can obtain the optimal investment policy under the CEI model by solving the RCEI model with $J = 1$, $\alpha(s^1) = \alpha$ and $K(s^1) = K$. For the CEI model, we set the threshold $\alpha = 0.005$ and the cardinality upper bound $K = 10$. All parameters in the partial penalty proximal ADMM are set as: the initial penalty parameter $\mu^1 = 2$, the initial penalty in ADMM $\beta^1 = 2$, the growth coefficient $\gamma = 1.4$, the proximal coefficient $\sigma = 1.3$, the external and internal tolerances are 10^{-5} and 10^{-3}, respectively.

Figure 1 shows the out-of-sample cumulative return rates of the optimal tracking portfolios derived by the RCEI and CEI models in FTSE 100, compared with the cumulative return rates of the FTSE 100 index.

Figure 2 shows the out-of-sample cumulative return rates of the optimal tracking portfolios derived by the RCEI and CEI models in S&P 500, compared with the cumulative return rates of the S&P 500 index.

We can see from Figures 1 and 2 that both optimal portfolios obtained from the RCEI and CEI models can efficiently track the trend of the market index and even outperform the market index. Meanwhile, the out-of-sample performances of the RCEI models are better than those of the CEI models or the indices in FTSE 100 and S&P 500 markets, respectively. The cumulative return rates of the optimal portfolios from the RCEI models are substantially higher than those from the CEI models and the market indices in UK and US financial markets. In addition, the optimal portfolios obtained from the RCEI model secure more stable returns and thus avoid substantial losses in a long-term investment process.

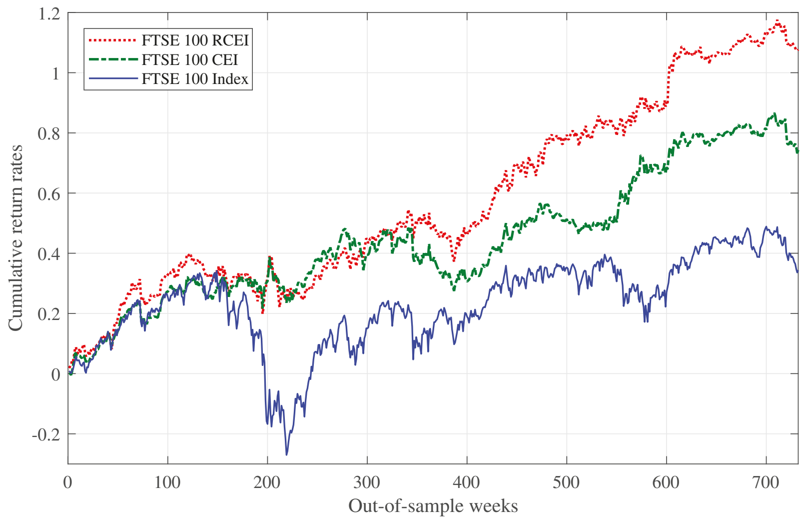

Figure 1. Out-of-sample performances of RCEI and CEI models in FTSE 100.

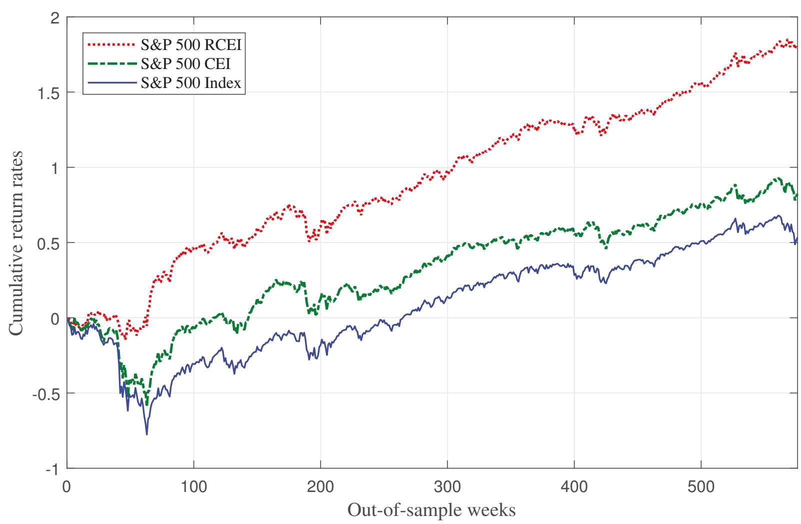

Figure 2. Out-of-sample performances of RCEI and CEI models in S&P 500.

For more details, we show typical statistics of weekly return rates of out-of-sample portfolios as well as the average CPU time in Table 3.

Table 3 shows that the means of the return rates of the RCEI and CEI models are much larger than that of the index, especially the RCEI model. In addition, the standard deviation of the RCEI and CEI models are smaller than that of the FTSE 100 index and close to that of the S&P 500 index, respectively. Sharpe ratio (SR) is a widely adopted indicator for calculating the risk-adjusted return, which can be used to evaluate a portfolio's performance. We can see from Table 3 that, in both financial markets, the Sharpe ratio value of the optimal portfolios from the RCEI models are larger than those of the CEI models or the market indices, respectively. It means that, in terms of the risk-adjusted return, the RCEI model also outperforms the CEI model and the market index.

Table 3. Statistics of out-of-sample portfolio return rates of RCEI and CEI models.

Index	Model	Mean	Std	SR	MDD	TE_+	TE_-	Time(s)
FTSE 100	RCEI	0.0015	0.0158	0.0931	0.2522	0.0067	0.0057	1.07
	CEI	0.0010	0.0143	0.0709	0.5918	0.0063	0.0057	1.10
	Index	0.0005	0.0224	0.0209	0.7717	-	-	-
S&P 500	RCEI	0.0031	0.0220	0.1425	0.1986	0.0060	0.0038	18.79
	CEI	0.0014	0.0258	0.0553	0.2104	0.0041	0.0036	18.94
	Index	0.0009	0.0254	0.0364	0.6117	-	-	-

Considering the financial sustainability in the long run, we calculate the maximum drawdown (MDD) [32] for each optimal portfolio of each model and the index in FTSE 100 and S&P 500. MDD is the maximum loss from a peak to a trough of a portfolio before a new peak is attained. It is an indicator of downside risk over a specific time period. We can see from Table 3 that the MDD value of the RCEI model is obviously smaller than those of the CEI model and the market index. It means that, when we obtain excess returns by the RCEI model, we can simultaneously avoid heavy losses for more than ten years. It is very important for the financial sustainability. In particular, a heavy loss is a big blow for any investor, which will result in the unsustainability in financial investments.

Table 3 also reveals that the expectation of the positive part of the tracking error i.e., $\mathrm{TE}_+ = \mathbb{E}[(R^\top x - R_I)_+]$, and the expectation of the negative part of the tracking error, i.e., $\mathrm{TE}_- = \mathbb{E}[(R^\top x - R_I)_-]$. In terms of TE_+ and TE_-, the performance of the RCEI model is better than that of the CEI model. Moreover, the proposed partial penalty proximal ADMM algorithm is highly efficient as the average CPU time is about 1 s in FTSE 100 enhanced problems and about 18 s in S&P 500 enhanced problems.

Furthermore, we divide the out-of-sample period of FTSE 100 and S&P 500 into three market regimes, respectively. Then, we compute the statistics of weekly return rates of the optimal portfolios under different market regimes, shown in Table 4.

In Table 4, we not only list the performance of the RCEI model under each market regime, but also that of the CEI model. We find that both RCEI and CEI models perform differently under different market regimes. Comparing with the CEI model, the RCEI model performs better in terms of the means, standard deviations and Sharpe ratios. In addition, the discrimination of the RCEI model in three market regimes are larger, which means that the RCEI model can describe the influence of different market regimes efficiently. In addition, in the bear market environment, the performance of the RECI model is better than that of the market index, which can avoid suffering a huge financial loss, and guarantee the sustainability of the investment consequently. It illustrates that the regime switching plays a fundamental role in financial sustainability.

Finally, we consider the effect of the cardinality constraint in the RCEI model. We test a reference of the RCEI model by removing the cardinality constraint, denoted by the REI model. We carry out the out-of-sample test for the REI model in a similar rolling forward way. Some statistics of out-of-sample weekly return rates of optimal portfolios determined by the RCEI and REI models are shown in Table 5. The average number of actually invested stocks in the corresponding optimal portfolios as well as the average CPU time are also shown in Table 5.

We can observe from Table 5 that, comparing with the REI model, the optimal portfolio obtained from the RCEI model could significantly reduce the number of really invested stocks without losing too much performance. Limiting the number of actually invested stocks is crucial in financial management due to the following reasons. Firstly, the transaction cost is high relative to the number of stocks we buy or sell. If we reduce the number of stocks in the indexation portfolio, we can save much capital in the transaction cost. Secondly, as fund managers or individual investors, it is impossible for them to manage dozens or hundreds of stocks at the same time, which can be regarded as another kind of manpower cost. This further proves that the RCEI model is sustainable in long-term financial investment problems if we take transaction costs into account.

Table 4. Statistics of the out-of-sample return rates under different market regimes.

Index	Model	State	Mean	Std	SR	TE_{+}	TE_{-}
FTSE 100	RCEI	Bull	0.0030	0.0142	0.2149	0.0053	0.0058
		Consolidation	0.0015	0.0147	0.1006	0.0056	0.0051
		Bear	−0.0014	0.0202	−0.0678	0.0118	0.0068
	CEI	Bull	0.0025	0.0120	0.2114	0.0048	0.0058
		Consolidation	0.0003	0.0136	0.0243	0.0049	0.0056
		Bear	−0.0001	0.0191	−0.0058	0.0122	0.0059
	Index	Bull	0.0036	0.0187	0.1902	-	-
		Consolidation	0.0010	0.0195	0.0518	-	-
		Bear	−0.0063	0.0318	−0.3328	-	-
S&P 500	RCEI	Bull	0.0040	0.0184	0.2148	0.0031	0.0031
		Consolidation	0.0032	0.0241	0.1343	0.0055	0.0028
		Bear	0.0005	0.0253	0.0193	0.0158	0.0088
	CEI	Bull	0.0032	0.0206	0.1579	0.0033	0.0034
		Consolidation	0.0024	0.0235	0.1017	0.0045	0.0035
		Bear	−0.0056	0.0393	−0.1419	0.0059	0.0044
	Index	Bull	0.0033	0.0190	0.1731	-	-
		Consolidation	0.0014	0.0240	0.0591	-	-
		Bear	−0.0071	0.0396	−0.1803	-	-

Table 5. Statistics of out-of-sample return rates of RCEI and REI models.

Index	Model	Mean	Std	SR	TE_{+}	TE_{-}	Stocks	Time(s)
FTSE 100	RCEI	0.0015	0.0158	0.0931	0.0067	0.0057	9.36	1.07
	REI	0.0017	0.0173	0.0974	0.0071	0.0061	88.75	0.06
S&P 500	RCEI	0.0031	0.0220	0.1425	0.0060	0.0038	9.67	18.79
	REI	0.0036	0.0282	0.1277	0.0104	0.0083	383.17	0.83

The average CPU time shows that the computational cost of the REI model is lower than that of the RCEI model. The reason is that we need to introduce some auxiliary variables and extra computation for dealing with the cardinality constraint, which not only increase the dimension of the problem but also increase the number of iterations for obtaining the optimal solution. Fortunately, the computation time of the RCEI model is quite acceptable even if we deal with 500 constituent stocks in the S&P 500 case.

5. Conclusions

In this paper, we propose a new sustainability-oriented enhanced indexation model with regime switching and cardinality constraint. By adopting the regime switching technique, we can flexibly set different risk thresholdsbenchmarks and cardinality bounds in different market environments, which can mirror the fluctuation of market environment in a timely manner. We solve the resulting deterministic optimization problem by the partial penalty proximal ADMM, which can deal with the cardinality constraint optimization problem in an acceptable computation time. In addition, we examine the performance of the proposed RCEI model in different financial markets and compare the out-of-sample results with FTSE 100 and S&P 500 indices, respectively. The numerical results show that the optimal portfolios obtained from the RCEI model have higher accumulative return and lower risk compared with those obtained from the CEI model and the market indices in the long-term investment process. At the same time, the invested stocks can be streamlined without losing much performance by adopting our proposed model and algorithm.

This innovative work fuels our conviction that the proposed model and algorithm are highly compatible with sustainable strategies, and investors can reap significant benefits from their joint cooperation. The accumulating evidence about the benefits of investment strategies would cultivate the growth of a sustainable investing market. Firstly, fund managers and individual investors can choose different threshold parameters and cardinality bounds in various financial markets. Risk-preference investors can set the semi-absolute tracking error threshold larger for higher excess returns. Risk-aversion ones who pursue a more secure return can set the threshold smaller. Fund managers and individual investors can also adjust the cardinality bounds according to their needs. Based on our experiences, cardinality bounds are suggested as no more than 20 for fund mangers and no more than 10 for individual investors. Secondly, our proposed model is more effective in mature financial markets. It should be used with caution in emerging financial markets which are less effective. To speak plainly, arbitrage opportunities will often occur in emerging markets; therefore, the optimal value may go to infinity. However, this is not consistent with the facts. In addition, mature financial markets provide more products that can be taken into account in our portfolios, such that investors can still maintain positive income by holding some short positions when the market is slow. In general, our method echoes sustainable growth in long-term investment processes.

This work can further be improved such as using another tracking error measure instead of the lower semi-absolute measure or extending the model to the multi-period case. These promising topics are left for future research.

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The Three Musketeers Relationships between Hong Kong, Shanghai and Shenzhen Before and After Shanghai–Hong Kong Stock Connect

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Abstract: This study examines the sustainability of financial integration between China (represented by Shenzhen and Shanghai) stock markets and Hong Kong stock market over the period of pre and post launch of the Stock Connect Scheme. This paper aims to fill the gap in the financial literature by providing empirical research on the dynamics of the financial integration process, and examining the sustainability of financial integration among the three Chinese stock markets. We apply cointegration and both linear and nonlinear causalities to investigate whether the Shanghai–Hong Kong Stock Connect has any impact on both market capitalizations and market indices of Hong Kong, Shanghai, and Shenzhen markets. Through cointegration tests and linear Granger causality techniques, it was found that the stock markets from mainland China are increasingly influencing the Hong Kong stock market after the introduction of the Stock Connect Scheme; however, when using nonlinear Granger causality analysis for confirming China market dominance, the result shows an reverse relationship whereby the Hong Kong stock market is still relevant to understand and predict China stock market after the introduction of the Stock Connect Scheme. Overall, our findings support the view that the Shanghai–Hong Kong Stock Connect has a significant impact on both market capitalizations and market indices of the Hong Kong, Shanghai, and Shenzhen markets, but Hong Kong stock market is still relevant to understand and predict China stock market after the introduction of the Stock Connect Scheme. The change in share premium difference between mainland China's domestic A-share markets and Hong Kong's H-share market could change investors' appetites or sentiments. Further research includes examining whether there is any functional relationship including nonlinear relationship and studying the dynamic drivers of the relationships.

Keywords: financial integration; cointegration; error correction; linear and nonlinear causality

1. Introduction

Stock market integration is an area of considerable interest and debate among academics and market practitioners. With regard to mainland China, where there has been continuous financial reform in terms of market deregulation and an aggressive pro-growth strategy, integration with neighboring markets has intensified, and whether integration can sustain better, in particular with Hong Kong. Given their economic similarities, the financial integration of mainland China's stock markets, Shanghai and Shenzhen, and that of Hong Kong has made remarkable progress over the past 10 years. In 2002 and 2006, the China Securities Regulatory Commission (CSRC) took to the airwaves, preempting the global financial media, to announce the Qualified Foreign Institutional Investor (QFII) and Qualified Domestic Institutional Investor (QDII) schemes respectively. The QFII scheme, under the existing restricted flow of capital accounts in China, allows qualified investors to invest in certain security products in China. In May 2007, the QDII scheme, which initially permitted Chinese institutions and residents to invest in fixed-income and money-market products overseas, was widened to include equity products in designated stock markets. These two arrangements have further increased the integration of mainland China and Hong Kong. The latter, the stock market of which is ranked as the seventh largest in the world and the third largest in Asia in terms of market capitalization (The World Federation of Exchanges and Bloomberg, June 2017), is a Special Administrative Region of China and a major financial center. Moreover, Hong Kong is committed to strengthening financial integration among the stock markets in China and make the integration sustains better. Financial theory suggests that an integrated regional market performs more efficiently than segmented individual market. Member markets can enhance the efficient allocation of capital in regions where the funding requirement is greatest. The attraction of cross-border fund flows is that they can improve the markets' liquidity and lower the cost of capital for firms [1]. The study on presence of herd formation in Chinese markets supports rational asset pricing models and market efficiency [2]. The general cointegration relationship between the prices of H-shares and A-shares, which are cross-listed Chinese stocks in both markets, across January 1999 to March 2009. It is found that significant improvements in the long-run expectation of H-share discounts compared with A-shares, the level of short-run co-movements in prices, and the magnitude of error corrections [3]. By applying stock market capitalization as a measure to identify countries that are taking the lead in establishing an integrated stock market in the Asia–Pacific region, the authors conclude that China and Hong Kong are the potential market leaders among other advanced equity markets (Japan, Australia, Singapore, and New Zealand). The reason is that China and Hong Kong exhibit unidirectional causality toward the other markets [4]. There is an increase in market integration among the different stock markets in the Greater China region, (China, Hong Kong, and Taiwan) from July 1993 to June 2013. Further, less volatile and sensitive responsiveness indicate improved stock market efficiency among the markets due to improved regulatory frameworks and better macroprudential policies, thereby enabling the more efficient absorption of market information [5].

The economies of Shanghai, Shenzhen, and Hong Kong constitute one of the most dynamic economic zones in the region. With closer trade and financial interaction, such as the QFII, QDII, RQFII, and RQDII (the Renminbi QFII and the Renminbi QDII respectively), the Shanghai–Hong Kong Stock Connect in 2014, and the Shenzhen–Hong Kong Stock Connect arrangement in 2016, the interaction of the Chinese stock markets has become a topic of global interest. However, there is a need for additional analysis regarding the nature and strength of these financial linkages. Although considerable researches have been conducted to investigate financial integration among East Asian countries and the effects on other world markets, little work has been conducted on the important aspect of financial linkages within China and the sustainability of financial integration within China. Further, given the geographic and economic closeness between the two regions of mainland China and Hong Kong, each of which could have significant influence over the other through increasing interaction [6,7], the current study fills the gap in the financial literature by providing empirical research on the dynamics of the financial integration process and examine the sustainability of financial integration among the three Chinese stock markets. In addition, this study enables us to discover the market leader within the country. The identification of the potential market leader can help policymakers to ensure policy coordination, enhance market development, and maintain market stability in the event of financial turmoil among the three stock markets. Given the decreasing benefit of diversification among these markets, this study is also of interest to investment practitioners when they allocate assets. The 'Stock Connect' Scheme appeared to provide a turning point in China's financial market development. It represents a remarkable move to the quality and sustainability of the growth for China's stock markets. The long-term objective of the scheme is to reorient growth to make it more balanced and more sustainable from different perspectives, such as market structure, connections with international practices and investors. It is a promising sign of push for reform to increase foreign investors' access to China's capital markets. Each of these moves had broader significance for ensuring a continue development and sustainable growth through policy reforms.

In this study, we use cointegration, linear and nonlinear causalities to investigate whether the Shanghai–Hong Kong Stock Connect has any impact on the market capitalizations and market indices of the Hong Kong, Shanghai, and Shenzhen markets. Our study deviates from the time series of the literature, which primarily examine nonlinear causal relationships using nonlinear causality tests. The nonlinear causality test can detect a nonlinear deterministic process that originally "looks" random. The nonlinear causality test used in the current study could be considered a complementary test for the linear causality test because the latter cannot detect a nonlinear type of causal relationship. The nonparametric approach adopted in this study can capture the nonlinear nature of the relationship between stock markets. The approach would not be mis-specified if the two variables, *market capitalization* and *market index*, are related nonlinearly or if regime changes (structural breaks) occur due to a crisis. We will discuss this issue further in the methodology section.

The remaining of the paper is structured as follows. Section 2 provides background information on the Shanghai–Hong Kong Stock Connect scheme. In Section 3, we present a review of the relevant literature regarding financial integration. The limitations of these studies are also noted. Section 4 describes the data and the methodology. The empirical results regarding both linear and nonlinear causality among various stock markets are discussed in Section 5. Section 6 concludes the paper.

2. Characteristics of the Shanghai–Hong Kong Stock Connect

The year 2015 marked a breakthrough in the Chinese and Hong Kong stock markets. The implementation of the Shanghai–Hong Kong Stock Connect allowed international investors direct access to the Shanghai stock market through the Hong Kong Stock Exchange. This initiative enables northbound and southbound trading within aggregate quotas of RMB300 billion and RMB250 billion, respectively. The quotas are calculated on a netting basis at the end of each trading day. Under the scheme, the daily quotas set a limit for daily net buy value of cross-boundary trades. The northbound daily quota is around RMB13 billion, while the southbound daily quota is around RMB10.5 billion. Under the scheme, except B-shares and shares included on the Risk Alert Board, investors can trade certain stocks listed on the Shanghai Stock Exchange that are not included as constituent stocks of the relevant indices but have corresponding H-shares listed in Hong Kong. The scheme also indicates that only mainland institutional investors and individual investors who have RMB500,000 in their accounts are allowed to trade stocks of the Hang Seng Composite Large Cap Index and Hang Seng Composite MidCap Index together with all H-shares that are not stocks of the relevant indices but have corresponding A-shares listed in Shanghai, except for those not traded in Hong Kong dollars and H-shares that are not listed in Shanghai. The Shanghai–Hong Kong Stock Connect helps to create a "single" stock market that ranks as the second and third largest worldwide in terms of market capitalization and turnover value respectively.

3. Literature Review

The first study in this area date back to the late 1980s and early 1990s, which apply the cointegration model to study the relationship between two stock markets [4,8–10]. Following this research, a substantial number of studies have focused on the degree of integration among different markets within geographic regions and the connections between international markets. The study on international stock-price linkages and co-movements of fundamentals within a multivariate cointegration framework finds that a common stochastic trend in the US, Canada, Germany, Japan, and the UK [11]. While studying the stock market linkages of a group of Pacific-Basin countries with US and Japan by estimating the multivariate cointegration model, it is suggested that the relaxation of the restrictions might have strengthened international market interrelations [12]. Furthermore, the four markets in Latin America (Argentina, Brazil, Chile, and Mexico), together with the US stock market, have significant permanent components that cause cointegration in the long run [13]. In other direction, the transmission of shocks between the U.S. and foreign markets to delineate interdependence from contagion of the US financial crisis by constructing shock models for partially overlapping and non-overlapping markets is examined [14]. The center of gravity within stock market integration studies has also moved from the markets in the Western hemisphere to the market linkages in Asian emerging markets, particularly for the periods before and after the 1997–98 Asian financial crisis. For example, the dynamic linkages of Asian stock markets before and after the crisis are examined. It is revealed that the relationships among East Asian stock markets are time-varying; for instance, Hong Kong and Singapore responded significantly sooner to the financial turmoil that was occurring in most Asian markets. More importantly, the empirical findings about the degree of stock market integration vary [15–18]. The linkages among the Southeast Asian stock markets are examined too and it is found that no evidence of a long-term relationship among the stock markets from 1988 to 1997; however, the degree of integration increases when the author conducts a correlation analysis. The results show that the returns of Indonesia, the Philippines, and Thailand were closely affected by the Singaporean market [19]. The long-term equilibrium relationships and short-term causality effects among stock markets in the US, Japan are investigated, and 10 other Asian economies, including Hong Kong, from January 1995 to May 2001. It is found that cointegration relationships both before and after the Asian financial crisis. Further, it is concluded that the degree of integration within the region increased after the crisis [20]. The degree of financial integration among selected East Asian countries from 1988 to 2006 by applying the panel unit root and cointegration approach is investigated too. The results show that high-income countries have better financial integration than middle-income countries and the sustainability of financial integration is better for high-income countries than middle-income countries [21]. The stock market integration in Asia is examined and it is found that the degrees of integration between mature and emerging equity markets differ. It is also shown that individual stock markets in Asia are more sensitive to regional events compared with global events. The difference in mature and emerging equity markets is mainly due to political, economic, and institutional issues [22]. As we can see, the above studies have a common characteristic: the comparisons are focused on different nations from a cross-country border perspective. Moreover, few studies have investigated different economies within China. The current study focuses on this less-visited field and fills the gap in the literature.

Nevertheless, there are a few related studies. The causal linkages among the Shanghai, Shenzhen, and Hong Kong stock markets are examined and it is found that the stock index series is non-stationary and that cointegrating vectors and error correction models do not exist for the index series. It is concluded that Granger causality shows a positive feedback mechanism from Shenzhen to Shanghai, while Hong Kong causes volatility in Shanghai but not vice versa [23]. By employing the daily values of the stock-price indices for the Shanghai, Shenzhen, and Hong Kong markets from 1992 to 2002, potential gains of intermarket timing for Hong Kong investors are found [24]. The financial integration in the Greater China region (China, Taiwan, and Hong Kong) is examined, it is indicated that a trend of increasing financial interaction in the region [25]. The China's A-share market and Hong Kong's stock market are closely integrated; however, there is little evidence to link them to the world market [26–28]. A similar study shows that at the time of their research, there was a spillover effect between the markets in the region and that the Chinese market was affected by its neighbors [7].

The impact of the Shanghai–Hong Kong Stock Connect is examined by using a pairwise linear causality test to check linear causal relationships between the closing prices of the SSE Composite Index and the Hong Kong Hang Seng Index (HSI). The authors find that the SSE takes a leading role after the implementation of Stock Connect Scheme [29]. The A- and H-share premium puzzle is investigated from the perspective of the effect of the Shanghai–Hong Kong Stock Connect policy. It is shown that the Shanghai–Hong Kong Stock Connect policy is effective at reducing the A- and H-share price gap [30]. A model of trading costs to consider the effect of the introduction of the Shanghai–Hong Kong Stock Connect is applied. It is found that the SSE, which may have had lower trading costs than those of the

Hong Kong Stock Exchange, seems to have developed higher trading costs in the period leading to the Stock Connect's introduction [31]. The variations in dependence and risk spillover between Chinese and London stock markets before and after Shanghai–Hong Kong Stock Connect and Shenzhen–Hong Kong Stock Connect are investigated, it is found that Shanghai–Hong Kong Stock Connect program enhances the dependence between Chinese and London stock markets, while the overall dependence decreases slightly after the Shenzhen–Hong Kong Stock Connect program [32].

4. Data and Methodology

4.1. Data Description

We use the daily stock market capitalizations and market indices of Hong Kong, Shanghai, and Shenzhen from January 2005 to December 2016, a total of 2817 observations. The data employed in the analysis is obtained from Bloomberg Financial Services. The data is divided into the following two data sets: 1) the "before" period from January 2005 to November 2014, which is the period before the Shanghai–Hong Kong Stock Connect, and 2) the "after" period from November 2014 to December 2016, which is the period after the Shanghai–Hong Kong Stock Connect. The starting point in 2005 marked an important milestone for Chinese stock market reform because it was then that China started changing its state-owned securities into tradable shares.

Table 1 shows the descriptive statistics for the three markets before and after the introduction of the Shanghai–Hong Kong Stock Connect. Hong Kong has the largest market capitalization and market index in both periods. The Shanghai stock market has the largest standard deviation for market capitalization and Hong Kong has the largest standard deviation for market index. In addition, market capitalization and market index are skewed in both periods. Excess kurtosis is deemed to be kurtosis greater than 3 for both of the variables and all markets, except for the variables of Hong Kong and Shenzhen in the "before" period and Hong Kong's market index in the "after period." We use the Jarque–Bera (JB) test to examine whether the data are normally distributed. Both market capitalization and market index are rejected to be normally distributed in both of the periods and all markets.

Table 1. Descriptive Statistics for Stock Market Capitalizations and Market Indices.

	Market Capitalization			**Market Index**		
	Hong Kong	**Shanghai**	**Shenzhen**	**Hong Kong**	**Shanghai**	**Shenzhen**
Before						
Mean	2149.56	1999.64	485.12	2603.88	364.12	133.30
Maximum	3424.25	3891.59	864.10	4082.25	810.67	223.21
Minimum	818.13	254.36	99.97	1420.72	122.21	28.66
Std. Dev.	694.35	915.89	196.73	464.31	131.82	53.71
Skewness	−0.40 ***	−0.85 ***	−0.82 ***	−0.30 ***	0.44 ***	−0.70 ***
Kurtosis	2.03 ***	−7.06 ***	2.41 ***	2.69 ***	3.93 ***	2.21 ***
Jarque–Bera	153.81 ***	306.93 ***	292.79 ***	43.184 ***	156.95 ***	247.58 ***
After						
Mean	3249.04	4274.35	1065.69	2954.59	518.35	306.35
Maximum	4069.50	6623.38	1684.08	3669.84	832.07	505.82
Minimum	2665.16	3002.20	752.91	2373.58	400.53	215.68
Std. Dev.	300.25	679.62	163.69	292.65	94.27	53.67
Skewness	0.91 ***	1.32 ***	1.46 ***	0.49 ***	1.40 ***	1.33 ***
Kurtosis	3.70 ***	4.58 ***	5.79 ***	2.81	4.37 ***	5.53 ***
Jarque–Bera	80.22 ***	197.98 ***	341.85 ***	21.04 ***	204.03 ***	282.46 ***

Notes: The figures for market capitalizations and market indices are in US billion dollars. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The normalized time series for market capitalizations and market indices in the three markets for both periods are plotted in Figure 1. The figure shows that the variables are moving closer after the introduction of the Shanghai–Hong Kong Stock Connect in November 2014.

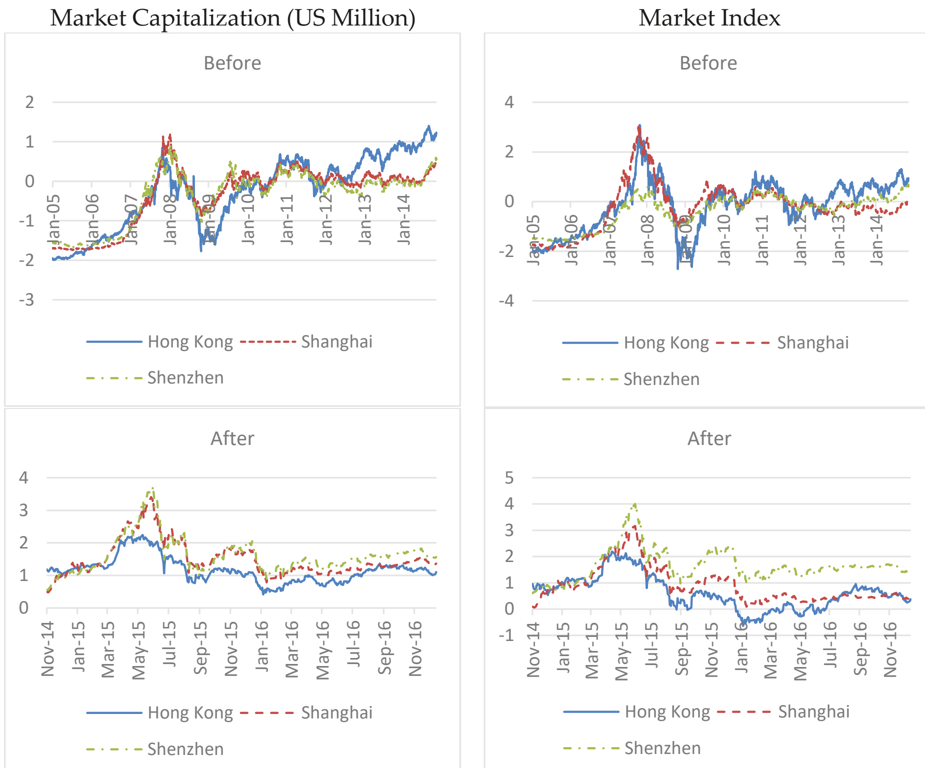

Figure 1. Shanghai, Shenzhen, and Hong Kong Stock Market Capitalizations and Market Indices.

4.2. Methodology

4.2.1. Cointegration

We conduct bivariate and multivariate cointegration for our variables. In order to estimate the long-run relationship between x_t and y_t, we first employ the following simple cointegration:

$$y_t = \beta_0 + \beta_1 x_t + e_t, \quad (1)$$

where y_t represents either the Hong Kong stock index or its market capitalization, x_t represents either the stock index or its market capitalization in Shanghai or the Shenzhen stock markets, and e_t is the residual for $t = 1, \ldots, T$. The test examines the residuals in regression (1) of I (1) variables. If x_t and y_t are I (1) and cointegrated, e_t is I (0). This finding means that the error term is stationary. Integration implies that a long-term linear relationship exists between series x_t and y_t.

In order to establish whether there is any cointegration relationship between the two vectors of the time series, we use three variables: $x_t = (x_{1,t}, x_{2,t})'$ and $y_t = (y_t)'$, where y_t represents either the Hong Kong stock index or its market capitalization, $x_{1,t}$ represents either the Shanghai stock index or its market capitalization, and $x_{2,t}$ represents either the Shenzhen stock index or its market capitalization. If all the variables $(x_{1,t}, x_{2,t}, y_t)$ are integrated in degree one, academics and practitioners will be interested to examine whether any cointegration relationship exists among them. In order to analyze this issue, we employ the Johansen cointegration test to estimate the cointegrating vectors [33–35]. According to Johansen's procedure, the p-dimensional unrestricted vector autoregression (VAR) model should be first specified with k lags as follows:

$$Z_t = \sum_{1}^{k} A_i Z_{t-i} + \Psi D_t + U_t, \tag{2}$$

where $Z_t = [x_{1,t},\ x_{2,t}, y_t]'$ is a 3×1 vector of stochastic variables, D_t is a vector of dummies, and A_i is an $\mathrm{n} \times \mathrm{n}$ matrix. If U_t is found to be a vector of I (0) residuals, a vector error correction model (VECM) could be constructed as follows:

$$\Delta Z_t = \sum_{1}^{k-1} \Phi_i \Delta Z_{t-1} + \Pi Z_{t-1} + \Psi D_t + U_t. \tag{3}$$

The hypothesis of cointegration is formulated as a reduced rank of the Π matrix. If the rank of Π (r) is less than or equal to 2, such that $\Pi = \alpha\beta'$ and $\Pi Z_{t-1} \sim I(0)$, r cointegrating vectors exist in β and the last (3-r) columns of the speed adjustment coefficients or loadings in α are zero [10]. Therefore, the matrix $\beta' Z_t$ constitutes r cointegrating equations and $\beta' Z_{t-1}$ represents r disequilibrium error terms.

In order to conduct the cointegration test, we employ the likelihood ratio (LR) reduced rank test for the null hypothesis of, at most, r cointegrating vectors, which is given by the trace statistic, λ_{trace}. Moreover, the null hypothesis of r against the alternative of r–1 cointegrating vectors is known as the maximal eigenvalue statistic, λ_{max}, as shown in the following:

$$\lambda_{trace} = -\mathrm{T} \sum_{i=r+1}^{n} \ln(1-\lambda_i),\ \lambda_{max} = -\mathrm{T}\ln(1-\lambda_i), \tag{4}$$

where $\lambda_i > \ldots > \lambda_3$ denotes three eigenvalues of the corresponding eigenvectors.

4.2.2. Linear Granger Causality

If two I (1) vectors, x_t and y_t, are cointegrated, the following error-correction mechanism (ECM) should be used to test Granger causality between the variables of interest:

$$\begin{pmatrix} \Delta x_t \\ \Delta y_t \end{pmatrix} = \begin{pmatrix} A_{x[2\times1]} \\ A_{y[1\times1]} \end{pmatrix} + \begin{pmatrix} A_{xx}(L)_{[2\times2]} & A_{xy}(L)_{[2\times1]} \\ A_{yx}(L)_{[1\times2]} & A_{yy}(L)_{[1\times1]} \end{pmatrix} \begin{pmatrix} \Delta x_{t-1} \\ \Delta y_{t-1} \end{pmatrix} + \begin{pmatrix} \alpha_{x[2\times1]} \\ \alpha_{y[1\times1]} \end{pmatrix} \cdot ecm_{t-1} + \begin{pmatrix} e_{x,t} \\ e_{y,t} \end{pmatrix}, \tag{5}$$

where ecm_{t-1} is lag 1 of the error correction term, $\alpha_{x[2\times1]}$ and $\alpha_{y[1\times1]}$ are the coefficient vectors for the error correction term ecm_{t-1}, and $\Delta x_t = (\Delta x_{1,t},\ \Delta x_{2,t})'$ and $\Delta y_t = (\Delta y_t)'$ are the corresponding stationary differencing series. There are now two sources of causation of $y_t(x_t)$ by $x_t(y_t)$, either through the lagged dynamic terms, $\Delta x_{t-1}(\Delta y_{t-1})$, or through the error correction term, ecm_{t-1}. Thereafter, the null hypothesis, $H_0{:}A_{xy}(L) = 0\big(H_0 : A_{yx}(L) = 0\big)$ and/or $H_0{:}\alpha_x = 0\big(H_0\ :\ \alpha_y = 0\big)$, can be tested to identify the Granger causality relationship using the LR test. We will discuss testing the null hypotheses, $H_0^1 : A_{xy}(L) = 0$ and $H_0^2 :\ A_{yx}(L) = 0$, when two I (1) vectors, x_t and y_t, are not cointegrated.

However, if two I (1) vectors, x_t and y_t, are not cointegrated, the following VAR model should be used to test Granger causality between the variables of interest:

$$\begin{pmatrix} \Delta x_t \\ \Delta y_t \end{pmatrix} = \begin{pmatrix} A_{x[2\times1]} \\ A_{y[1\times1]} \end{pmatrix} + \begin{pmatrix} A_{xx}(L)_{[2\times2]} & A_{xy}(L)_{[2\times1]} \\ A_{yx}(L)_{[1\times2]} & A_{yy}(L)_{[1\times1]} \end{pmatrix} \begin{pmatrix} \Delta x_{t-1} \\ \Delta y_{t-1} \end{pmatrix} + \begin{pmatrix} e_{x,t} \\ e_{y,t} \end{pmatrix}, \tag{6}$$

where all the terms are defined in Equation (1). Testing the linear causality relationship between x_t and y_t is equivalent to testing the following null hypotheses: $H_0^1 : A_{xy}(L) = 0$ and $H_0^2 :\ A_{yx}(L) = 0$. There are four different situations for the causality relationships between x_t and y_t in (4): (a) rejecting H_0^1 but not rejecting H_0^2 implies a unidirectional causality from y_t to x_t, (b) rejecting H_0^2 but not rejecting H_0^1 implies a unidirectional causality from x_t to y_t, (c) rejecting both H_0^1 and H_0^2 implies the existence of feedback relations, and (d) not rejecting both H_0^1 and H_0^2 implies that x_t and y_t are not rejected as independent [36–38].

4.2.3. Nonlinear Granger Causality

The linear Granger causality test discussed in Section 4.2.2 is based on the assumption that the relationship between the variables is linear. In order to further investigate whether any nonlinear relationship exists between vectors x_t and y_t, we conduct a nonlinear causality test [36,37]. Evidence of nonlinear relationships between stock markets is found in various studies. For example, The evidence of significant nonlinear dependence in stock markets is found [39,40]. It is explained that the complex and chaotic dynamics are likely to emerge in different parts of an economic system [40]. Further, the pattern between different objectives may appear random following many statistical tests; however, a more effective result may be achieved by using tests that consider the possibility of a nonlinear pattern. Therefore, some nonlinear models have been developed in studies relating to economics and finance. For example, it is noticed that the nonlinear structure in stock-price movements is motivated by asset behavior that follows nonlinear models [41]. A nonparametric test is developed to detect the nonlinear causal relationship between two variables [42]. The nonlinear causality test to the multivariate setting is extended [36,37], and the test is further extended to panel data [38]. Nonlinear Granger causality are also applied by some other scholars [43,44].

In order to identify any nonlinear Granger causality relationship from any two vector series, $x_t = (x_{1,t},\ x_{2,t})'$ and $y_t = (y_t)'$, we first use the linear model for $\{x_t\}$ and $\{y_t\}$ to identify their linear causal relationships and obtain the corresponding residuals, $\{\hat{\varepsilon}_{1t}\}$ and $\{\hat{\varepsilon}_{2t}\}$. Thereafter, we apply a nonlinear Granger causality test to the residual series, $\{\hat{\varepsilon}_{1t}\}$ and $\{\hat{\varepsilon}_{2t}\}$, of the two examined variables to identify the remaining nonlinear causal relationships between their residuals. We denote $X_t = (X_{1,t}, \ldots, X_{n1,t})'$ and $Y_t = (Y_{1,t}, \ldots, Y_{n2,t})'$ to be the corresponding residuals of any two vectors of the examined variables.

We first define the lead vector and lag vector of a time series, say $X_{i,t}$, as follows: for

$X_{i,t}$, i $= 1, \ldots, n_1$, the m_{x_i}-length lead vector and the L_{x_i}-length lag vector of $X_{i,t}$ are
$X_{i,t}^{m_{x_i}} \equiv \left(X_{i,t}, X_{i,t+1}, \ldots, X_{i,t+m_{x_i}-1}\right), m_{x_i} = 1, 2, \ldots, t = 1,\ 2,\ \ldots,$ and
$X_{i,t-L_{x_i}}^{L_{x_i}} \equiv \left(X_{i,t-L_{x_i}}, X_{i,t-L_{x_i}+1}, \ldots, X_{i,t-1}\right), L_{x_i} = 1,\ 2,\ \ldots,\ \mathrm{t} = L_{x_i} + 1, L_{x_i} + 2, \ldots,$
respectively. We denote $M_x = \left(m_{x1}, \ldots, m_{x_{n_1}}\right)$, $L_x = \left(L_{x1}, \ldots, L_{x_{n_1}}\right)$, $m_x = \max(m_{x1}, \ldots, m_{n_1})$, and $l_x = \max\left(L_{x1}, \ldots, L_{x_{n_1}}\right)$.

The m_{y_i}-length lead vector, $Y_{i,t}^{m_{y_i}}$, the L_{y_i}-length lag vector, $Y_{i,t-L_{y_i}}^{L_{y_i}}$, of $Y_{i,t}$, and $M_y, L_y,\ m_y$, and l_y can be defined similarly.

Using this modeling approach, we extend [36,37,42,45] to derive the following statistic,

$$H = \sqrt{n}\left(\frac{C_1\left(M_x + L_x, L_y, e, n\right)}{C_2\left(L_x, L_y, e, n\right)} - \frac{C_3(M_x + L_x, e, n)}{C_4(L_x, e, n)}\right), \tag{7}$$

to test the null hypothesis, H_0, that $Y_t = (Y_{1,t}, \ldots, Y_{n2,t})'$ does not strictly Granger cause $X_t = (X_{1,t}, \ldots, X_{n1,t})'$. [37,38] have more information on the test statistic.

5. Empirical Results and Discussion

5.1. Unit Root Test

We employ the classical unit root augmented Dickey–Fuller (ADF) test to examine whether there is any unit root in the market capitalizations and the market indices for the "before" and "after periods" and for all markets by taking into consideration the following conditions: "without a constant and trend", "a constant", and "both a constant and trend". The results of the ADF tests are presented in Table 2. From the table, the null hypothesis that the series is non-stationary cannot be rejected for market capitalizations, market indices, and for all markets in both periods. However, the hypothesis that the first differences of market capitalizations and market indices are non-stationary is rejected in all markets and in both periods, regardless of allowing for a constant, both a constant and trend, or none of these. This suggests that market capitalizations and market indices are I (1) for all markets in both periods.

Table 2. ADF Unit Root Tests—Level and First Difference of Variables.

	Level			First Difference		
Variable/Market	**Without a Constant and Trend**	**With a Constant**	**With a Constant and Trend**	**Without a Constant and Trend**	**With a Constant**	**With a Constant and Trend**
Market Capitalization—Before						
Hong Kong	1.682711	−1.919425	−2.205666	−52.60101 ***	−52.65588 ***	−52.66070 ***
Shanghai	2.353194	−2.180448	−1.120584	−48.22354 ***	−48.34105 ***	−48.40782 ***
Shenzhen	1.694196	−1.698022	−1.354723	−45.59289 ***	−45.64103 ***	−45.65093 ***
Market Capitalization—After						
Hong Kong	−0.086144	−1.584134	−1.763568	−20.45296 ***	−20.43241 ***	−20.41225 ***
Shanghai	0.612571	−2.410414	−2.848671	−16.90724 ***	−16.91163 ***	−16.98909 ***
Shenzhen	0.627730	−2.566980	−2.583824	−20.38275 ***	−20.37833 ***	−20.41032 ***
Market Index—Before						
Hong Kong	0.626803	−2.371107	−2.637028	−49.52579 ***	−49.52618 ***	−49.51887 ***
Shanghai	1.066231	−1.934023	−1.517596	−47.77306 ***	−47.79211 ***	−47.81669 ***
Shenzhen	1.563084	−1.661637	−1.471991	−45.09358 ***	−45.14931 ***	−45.15690 ***
Market Index—After						
Hong Kong	−0.334852	−1.494780	−1.686786	−21.77970 ***	−21.76091 ***	−21.73916 ***
Shanghai	0.167181	−1.673607	−2.844149	−16.82485 ***	−16.81046 ***	−16.88770 ***
Shenzhen	0.456605	−2.337842	−2.277986	−20.02130 ***	−20.01022 ***	−20.04949 ***

Notes: The critical ADF values are based on one-sided p-value. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

5.2. Cointegration

Table 3 presents the results of the cointegration test for the market capitalizations and the major market indices of the Hong Kong, Shanghai, and Shenzhen markets in both periods, "before" and "after". In the Johansen cointegration test, different numbers of lags and different informational criteria could suggest different lag lengths for the explanatory variable; moreover, the different criteria could cause conflicting results. In order to circumvent this limitation, we use Lag 1 to Lag 4 when applying the Johansen cointegration test for each variable. With regard to market capitalization, the Hong Kong, Shanghai, and Shenzhen markets are cointegrated at the 10% significance level at least in the "before" and "after" periods. With regard to market indices, the Hong Kong, Shanghai, and Shenzhen markets are cointegrated at the 10% significance level at least in the "after" period and are not cointegrated in the "before" period. This finding infers that the Shanghai–Hong Kong Stock Connect has a significant impact on the market indices, but not on the market capitalizations, of the Hong Kong, Shanghai, and Shenzhen markets in the sense that the market indices of these markets become cointegrated after the introduction of the Shanghai–Hong Kong Stock Connect but are not cointegrated before its introduction. Nonetheless, the market capitalizations of the Hong Kong, Shanghai, and Shenzhen markets are cointegrated before and after the introduction of the Shanghai–Hong Kong Stock Connect. Alternatively, we can say that the introduction of the Shanghai–Hong Kong Stock Connect has no effect on the cointegration of the market capitalizations in the Hong Kong, Shanghai, and Shenzhen markets.

Table 3. The Johansen Cointegration Test.

	Trace statistic				Maximal Eigenvalue Statistic			
Lags	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Market Capitalization—Before								
	50.41438 ***	49.85247 ***	50.27316 ***	48.99552 **	26.82384 **	26.53612 **	27.53781 **	28.16635 **
Market Capitalization—After								
	40.62609 *	41.72919 *	43.53722 **	43.44726 **	23.51745 *	25.62289 *	25.46559 *	24.03629 *
Market Index—Before								
	31.64630	30.98641	30.39318	28.58406	15.41028	15.02911	14.67202	13.22303
Market Index—After								
	41.76066 *	43.02648 **	46.48707 **	47.99164 **	28.48594 **	29.83725 **	32.73789 ***	34.94959 ***

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

We conduct the Engle–Granger two-step cointegration test as a complementary analysis to the Johansen cointegration test. Table 4 presents the results for each of the variables and for different pairs of markets for the “before” and “after” periods. The results suggest that a cointegration relationship exists between Hong Kong and Shanghai and between Hong Kong and Shenzhen for the market capitalizations and market indices in the “after” period but not in the “before” period. These results are consistent with those in Table 3 and provide more information. First, the results of Tables 3 and 4 are the same for the market indices such that the Shanghai–Hong Kong Stock Connect has a significant impact on the market indices of the Hong Kong, Shanghai, and Shenzhen markets in the sense that the market indices of these markets become cointegrated after the introduction of the Shanghai–Hong Kong Stock Connect but are not cointegrated before its introduction.

Table 4. Cointegrations between Shanghai, Shenzhen, and Hong Kong.

Dependent Variable	Independent Variable	Tau-Statistic for ADF Test	
		Before	After
Market Capitalization			
Hong Kong	Shanghai	−1.807367	−3.702708 ***
Shanghai	Hong Kong	−1.812675	−3.697735 ***
Hong Kong	Shenzhen	−2.366831	−3.428527 ***
Shenzhen	Hong Kong	−2.375368	−3.422214 ***
Market Index			
Hong Kong	Shanghai	−1.909637	−2.507151 *
Shanghai	Hong Kong	−1.871656	−2.499474 *
Hong Kong	Shenzhen	−1.765747	−2.694529 *
Shenzhen	Hong Kong	−1.630341	−2.676564 *

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

However, Table 3 shows that the market capitalizations of the Hong Kong, Shanghai, and Shenzhen markets are cointegrated before and after the introduction of the Shanghai–Hong Kong Stock Connect, while Table 4 shows that the market capitalizations between the Hong Kong and Shanghai markets and between the Hong Kong and Shenzhen markets are cointegrated after, but not before, the introduction of the Shanghai–Hong Kong Stock Connect. Readers may regard these results as contradictory because Table 4 shows that the market capitalizations between the Hong Kong and Shanghai markets and between the Hong Kong and Shenzhen markets are not cointegrated before the introduction of the

Shanghai–Hong Kong Stock Connect, while Table 3 shows that the market capitalizations of the Hong Kong, Shanghai, and Shenzhen markets are cointegrated in the "before" period. Nonetheless, we note that the results are still consistent. For example, the market capitalization between Hong Kong and Shanghai is not cointegrated in the "before" period; however, after including Shenzhen, the market capitalizations of the Hong Kong, Shanghai, and Shenzhen markets are cointegrated in the "before" period. There is no contradiction. Overall, the results from Tables 3 and 4 conclude that the Shanghai–Hong Kong Stock Connect has a significant impact on the market indices and market capitalizations of the Hong Kong, Shanghai, and Shenzhen markets in the sense that in the pairings of Hong Kong–Shanghai and Hong Kong–Shenzhen, both variables are not cointegrated before the introduction of the Shanghai–Hong Kong Stock Connect but are cointegrated after its introduction. Nonetheless, the Shanghai–Hong Kong Stock Connect has a greater impact on the market indices of the Hong Kong, Shanghai, and Shenzhen markets in the sense that these market indices are not cointegrated before the introduction of the Shanghai–Hong Kong Stock Connect but are cointegrated after its introduction.

5.3. Linear Causality

Given the cointegration test results in Tables 3 and 4, we employ VECM and VAR for the multivariate linear Granger causality test for the corresponding return data. Namely, we use the VECM for market capitalizations in the "before" and "after" periods and for market indices in the "after" period. Further, we apply VAR for the market indices in the "before" period. Because linear Granger causality test results are sensitive to the chosen number of lags [1,46,47], we perform the test by applying Lag 1 to Lag 4 to ensure the persistence of the causality effect. Table 5 presents the results.

The results in Table 5 suggest that for market capitalizations, Shanghai and Shenzhen together strongly linear cause Hong Kong only in the "after" period; however, Hong Kong does not linear cause Shanghai and Shenzhen in the "before" and "after" periods. With regard to the market indices, Table 5 also indicates that Shanghai and Shenzhen together strongly linear cause Hong Kong in the "before" and "after" periods and that Hong Kong also strongly linear causes Shanghai and Shenzhen in the "before" period. In the "after" period, Hong Kong only weakly linear causes Shanghai and Shenzhen.

Table 5. Multivariate Linear Causality Test.

Lags	1	2	3	4
Market Capitalization—Before				
Shanghai, Shenzhen do not linear cause Hong Kong	7.38371	9.375204	10.72305	13.5075
Hong Kong does not linear cause Shanghai, Shenzhen	10.91606	11.3073	12.10023	15.50066
Market Capitalization—After				
Shanghai, Shenzhen do not linear cause Hong Kong	24.53035 ***	25.04021 ***	25.89332 **	27.30361 **
Hong Kong does not linear cause Shanghai, Shenzhen	7.541288	10.57955	10.38692	12.52102
Market Index—Before				
Shanghai, Shenzhen do not linear cause Hong Kong	29.53564 ***	32.25287 ***	41.44762 ***	45.33166 ***
Hong Kong does not linear cause Shanghai, Shenzhen	26.19195 ***	35.55226 ***	40.05167 ***	50.15208 ***
Market Index—After				
Shanghai, Shenzhen do not linear cause Hong Kong	16.33123 **	18.64942 **	21.32368 **	23.37843 *
Hong Kong does not linear cause Shanghai, Shenzhen	8.691268	15.81915 *	19.27024 *	22.04703

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Again, and as a complementary analysis to the multivariate linear causality tests for both variables, Tables 6 and 7 exhibit the results of the individual linear causality tests for each variable of different stock exchange pairs. The results in Table 6 suggest that for market capitalizations in the "before" period, Shenzhen strongly linear causes Hong Kong, while Hong Kong strongly linear causes Shanghai and weakly linear causes Shenzhen. In the "after" period, Table 6 suggests that Shanghai strongly linear causes Hong Kong, while Hong Kong strongly linear causes Shanghai and weakly linear causes Shenzhen.

Table 6. Pairwise Linear Granger Causality Test—Market Capitalizations.

Null Hypothesis (Before)	Lag 1	Lag 2	Lag 3	Lag 4
Shanghai does not linear cause Hong Kong	0.978580	2.012203	2.192758	2.387463
Hong Kong does not linear cause Shanghai	8.537985 ***	8.480986 **	9.559701 **	10.36996 **
Shenzhen does not linear cause Hong Kong	5.348578 **	6.381996 **	6.677565 *	8.543683 *
Hong Kong does not linear cause Shenzhen	5.051887 **	4.996726 *	4.784889	5.999298
Null Hypothesis (After)				
Shanghai does not linear cause Hong Kong	3.879897 **	5.268828 *	7.771181 *	11.00691 **
Hong Kong does not linear cause Shanghai	2.926277 *	4.441486	6.289897 *	8.776270 *
Shenzhen does not linear cause Hong Kong	0.012944	1.287811	1.721678	4.355685
Hong Kong does not linear cause Shenzhen	3.585345 *	4.261239	5.759532	10.40691 **

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The results in Table 7 suggest that for the market indices, both Shanghai and Shenzhen strongly linear cause Hong Kong separately, but Hong Kong does not linear cause either Shanghai or Shenzhen in the "before" period. In the "after" period, both Shanghai and Shenzhen do not linear cause Hong Kong separately and Hong Kong does not linear cause Shanghai or Shenzhen.

Table 7. Pairwise Linear Granger Causality Test—Market Indices.

Null Hypothesis (Before)	Lag 1	Lag 2	Lag 3	Lag 4
Shanghai does not linear cause Hong Kong	8.893183 ***	9.610947 ***	10.01526 ***	9.858900 **
Hong Kong does not linear cause Shanghai	1.427837	1.441529	1.406733	2.249378
Shenzhen does not linear cause Hong Kong	16.52512 ***	16.90540 ***	17.56947 ***	17.47762 ***
Hong Kong does not linear cause Shenzhen	0.191262	1.128381	1.054686	1.968744
Null Hypothesis (After)				
Shanghai does not linear cause Hong Kong	1.650946	3.070147	4.425512	6.041571
Hong Kong does not linear cause Shanghai	1.099184	3.331752	4.805973	5.678313
Shenzhen does not linear cause Hong Kong	0.309486	0.787259	0.978551	2.257896
Hong Kong does not linear cause Shenzhen	0.426839	0.524547	1.352728	2.567101

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 4 shows the results of the pairwise cointegrations. However, for those pairs of variables that are cointegrated, we have to include the speeds of the adjustments in the ECM linear Granger causality model in Equation (3). The estimates of the speeds of adjustments are given in Tables 8 and 9 for market capitalizations and market indices respectively. With regard to market capitalizations, the averages of the estimated speeds of adjustments in any market are smaller than 0.049 (in absolute value), implying that in general any movement away from the long-term equilibrium between the various market pairs is slow to correct. An estimate of 0.049, at the upper limit of the means, implies a 4.9% adjustment back to equilibrium in a given trading day. Similarly, for the market indices, the averages of the estimated speeds of adjustments in any market are smaller than 0.032 (in absolute value), implying that in general any movement away from the long-term equilibrium between the various market pairs is slow to correct. An estimate of 0.032, at the upper limit of the means, implies a 3.2% adjustment back to equilibrium in a given trading day.

Table 8. Speeds of Adjustments in the Linear Granger Causality Test—Market Capitalizations.

Null Hypothesis (Before)	**Lag 1**	**Lag 2**	**Lag 3**	**Lag 4**
Shanghai does not linear cause Hong Kong	n/a	n/a	n/a	n/a
Hong Kong does not linear cause Shanghai	n/a	n/a	n/a	n/a
Shenzhen does not linear cause Hong Kong	n/a	n/a	n/a	n/a
Hong Kong does not linear cause Shenzhen	n/a	n/a	n/a	n/a
Null Hypothesis (After)				
Shanghai does not linear cause Hong Kong	−0.004669	−0.005398	−0.006306	−0.006973
Hong Kong does not linear cause Shanghai	−0.044791 ***	−0.046493 ***	−0.048387 ***	−0.048581 ***
Shenzhen does not linear cause Hong Kong	−0.007094	−0.007855	−0.009215	−0.010231
Hong Kong does not linear cause Shenzhen	−0.039959 ***	−0.040460 ***	−0.042351 ***	−0.043781 ***

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 9. Speeds of Adjustments in the Linear Granger Causality Test—Market Indices.

Null Hypothesis (Before)	**Lag 1**	**Lag 2**	**Lag 3**	**Lag 4**
Shanghai does not linear cause Hong Kong	n/a	n/a	n/a	n/a
Hong Kong does not linear cause Shanghai	n/a	n/a	n/a	n/a
Shenzhen does not linear cause Hong Kong	n/a	n/a	n/a	n/a
Hong Kong does not linear cause Shenzhen	n/a	n/a	n/a	n/a
Null Hypothesis (After)				
Shanghai does not linear cause Hong Kong	−0.000644	−0.001230	−0.001977	−0.003281
Hong Kong does not linear cause Shanghai	−0.028955 ***	−0.029045 ***	−0.030224 ***	−0.031811 ***
Shenzhen does not linear cause Hong Kong	−0.003705	−0.004845	−0.006024	−0.007039
Hong Kong does not linear cause Shenzhen	−0.020618 ***	−0.021161 ***	−0.021848 ***	−0.023016 ***

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

5.4. Nonlinear Causality

We suggest that linear and nonlinear causality relationships could be independent in the sense that the existence of a linear causality relationship does not infer the existence of a nonlinear causality relationship and vice versa. Therefore, we propose investigating whether there is any change in nonlinear causality relationships after the introduction of the Shanghai–Hong Kong Stock Connect. Consequently, we report in Table 10 the results of the multivariate nonlinear Granger causality tests of different markets' market capitalizations and stock indices. We find that for market capitalizations and market indices, Shanghai and Shenzhen strongly nonlinearly cause Hong Kong in the "before" and "after" periods, while Hong Kong strongly nonlinearly causes Shanghai and Shenzhen in the "before" period and only weakly nonlinearly causes Shanghai and Shenzhen in the "after" period.

Table 10. Multivariate Nonlinear Causality Test.

Lags	1	2	3	4
Market Capitalization—Before				
Shanghai, Shenzhen do not nonlinearly cause Hong Kong	4.210291 ***	4.920050 ***	5.380364 ***	4.844110 ***
Hong Kong does not nonlinearly cause Shanghai, Shenzhen	4.687631 ***	5.005889 ***	5.065219 ***	4.561966 ***
Market Capitalization—After				
Shanghai, Shenzhen do not nonlinearly cause Hong Kong	2.116468 **	2.820839 ***	2.350409 ***	1.308816 *
Hong Kong does not nonlinearly cause Shanghai, Shenzhen	0.653933	1.520695 *	0.199958	0.971179
Market Index—Before				
Shanghai, Shenzhen do not nonlinearly cause Hong Kong	4.542631 ***	4.828466 ***	4.973165 ***	4.293640 ***
Hong Kong does not nonlinearly cause Shanghai, Shenzhen	5.358980 ***	5.774119 ***	4.827240 ***	5.010060 ***
Market Index—After				
Shanghai, Shenzhen do not nonlinearly cause Hong Kong	2.037944 **	2.242687 **	1.624614 *	1.186182
Hong Kong does not nonlinearly cause Shanghai, Shenzhen	−0.221909	0.426697	−0.855035	0.523144

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Again, and as a complementary analysis to the nonlinear Granger causality tests for all three stock exchanges, Tables 11 and 12 present the results of the individual nonlinear Granger causality tests for market capitalizations and the market indices respectively for each stock exchange pair. Table 11 suggests that for market capitalizations, Shanghai–Hong Kong and Shenzhen–Hong Kong are two interactive pairwise markets in which strong bi-directional nonlinear Granger causalities are found in the "before" period. In the "after" period, Table 11 suggests that Shanghai and Shenzhen strongly nonlinearly cause Hong Kong individually, while Hong Kong only weakly nonlinearly causes Shanghai and Shenzhen individually.

Table 11. Pairwise Nonlinear Causality Test—Market Capitalizations.

Null Hypothesis (Before)	**Lag 1**	**Lag 2**	**Lag 3**	**Lag 4**
Shanghai does not nonlinearly cause Hong Kong	3.795365 ***	4.551167 ***	5.164434 ***	4.694305 ***
Hong Kong does not nonlinearly cause Shanghai	4.619768 ***	5.187093 ***	5.304950 ***	4.865725 ***
Shenzhen does not nonlinearly cause Hong Kong	3.804926 ***	4.500830 ***	5.043632 ***	4.707949 ***
Hong Kong does not nonlinearly cause Shenzhen	4.225535 ***	5.039040 ***	5.194823 ***	4.742640 ***
Null Hypothesis (After)				
Shanghai does not nonlinearly cause Hong Kong	1.468207 *	2.749260 ***	2.277180 **	1.434418 *
Hong Kong does not nonlinearly cause Shanghai	0.800458	1.572935 *	0.540221	1.133238
Shenzhen does not nonlinearly cause Hong Kong	2.458619 ***	2.952265 ***	2.404669 ***	1.366114 *
Hong Kong does not nonlinearly cause Shenzhen	1.977940 **	2.261325 **	0.900703	1.065920

Notes: The *, **, and *** denote the significance at 10%, 5% and 1% levels, respectively.

With regard to the market indices, Table 12 suggests that Shanghai–Hong Kong and Shenzhen–Hong Kong are two interactive pairwise markets in which strong bi-directional nonlinear Granger causalities are found in the "before" period. In a similar way to market capitalizations (see Table 11), Table 12 indicates that Shanghai and Shenzhen strongly nonlinearly cause Hong Kong individually, while Hong Kong only weakly nonlinearly causes Shanghai and Shenzhen individually.

Table 12. Pairwise Nonlinear Causality Test—Market Indices.

Null Hypothesis (Before)	Lag 1	Lag 2	Lag 3	Lag 4
Shanghai does not nonlinearly cause Hong Kong	4.337560 ***	4.680782 ***	4.778670 ***	3.847159 ***
Hong Kong does not nonlinearly cause Shanghai	5.296137 ***	5.917483 ***	5.496391 ***	5.363044 ***
Shenzhen does not nonlinearly cause Hong Kong	3.972803 ***	4.353763 ***	4.490202 ***	4.149760 ***
Hong Kong does not nonlinearly cause Shenzhen	4.303810 ***	5.414131 ***	5.009831 ***	4.677395 ***
Null Hypothesis (After)				
Shanghai does not nonlinearly cause Hong Kong	1.565120 *	2.511137 ***	1.870381 **	1.411452 *
Hong Kong does not nonlinearly cause Shanghai	−0.117091	0.654299	−0.268652	0.819147
Shenzhen does not nonlinearly cause Hong Kong	2.348446 ***	2.349964 ***	1.817364 **	1.465420 *
Hong Kong does not nonlinearly cause Shenzhen	1.401143 *	1.890706 **	0.670792	0.896187

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

6. Conclusions

We summarize all our empirical results in Tables 13 and 14. Table 13 shows that for market capitalization, Shanghai and Shenzhen exist a high degree of cointegration with Hong Kong before and after the implementation of the Stock Connect Scheme. As for causality, the strong effect found before the rollout of the Scheme under the nonlinear analysis from Shanghai and Shenzhen to Hong Kong (SH, $SZ \Rightarrow HK$) remains unchanged during the post implementation period. However, the nonlinear causality effect from Hong Kong to Shanghai and Shenzhen ($HK \Rightarrow SH$, SZ) decreased after the implementation of the Stock Connect Scheme.

Table 13. Summary of Multivariate Test Results.

Variables	Cointegration	Causality	*SH, SZ⇒HK*	*HK⇒SH, SZ*
Market Capitalization (Before)	Strongly	Linear	x	x
		Nonlinear	strongly	strongly
Market Capitalization (After)	Strongly	Linear	strongly	x
		Nonlinear	strongly	weakly
Market Index (Before)	X	Linear	strongly	strongly
		Nonlinear	strongly	strongly
Market Index (After)	Strongly	Linear	strongly	weakly
		Nonlinear	strongly	x

Table 14. Summary of Pairwise Test Results.

Variables	Cointegration *SH with HK*	Cointegration *SZ with HK*	Causality	*SH⇒HK*	*SZ⇒HK*	*HK⇒SH*	*HK⇒SZ*
Market Capitalization (Before)	x	x	Linear	x	strongly	strongly	strongly
			Nonlinear	strongly	strongly	strongly	strongly
Market Capitalization (After)	✓	✓	Linear	strongly	x	strongly	strongly
			Nonlinear	strongly	strongly	weakly	strongly
Market Index (Before)	x	x	Linear	strongly	strongly	x	x
			Nonlinear	strongly	strongly	strongly	strongly
Market Index (After)	✓	✓	Linear	x	x	x	x
			Nonlinear	strongly	strongly	x	strongly

With regard to the market indices, no cointegration is found before the Stock Connect Scheme. However, Shanghai and Shenzhen exhibit a high degree of cointegration with Hong Kong after the rollout of the scheme. Regarding causality effect, a bi-directional causality relationship between Shanghai/Shenzhen and Hong Kong *(SH, SZ* Δ *HK)* is found before the rollout of the Stock Connect Scheme, despite whether it is obtained from linear or nonlinear analysis. However, such causality relationship is changed where a uni-directional causality from Shanghai and Shenzhen to Hong Kong ($SH, SZ \Rightarrow HK$) dominates after the implementation of the Stock Connect Scheme. Therefore, the causality effect from Hong Kong to Shanghai and Shenzhen ($HK \Rightarrow SH, SZ$) diminished after the rollout of the Scheme.

Table 14 shows the pairwise test results. From both market capitalization and market index perspectives, neither the Shanghai nor the Shenzhen market is cointegrated with Hong Kong market before the implementation of Stock Connect Scheme. However, on a pairwise base, cointegration relationships for Shanghai/Hong Kong and Shenzhen/Hong Kong are found after the rollout of the scheme. The findings from pairwise test support the view that the Stock Connect Scheme has a significant impact on both market capitalizations and market indices of the Hong Kong, Shanghai, and Shenzhen markets. The Hong Kong stock market is still relevant to understand and predict China stock market after the implementation of the Stock Connect Scheme.

This principal contribution of this study lies in the development of a model that makes it possible to capture the degree of integration between the Chinese and Hong Kong stock markets following the implementation of the Shanghai–Hong Kong Stock Connect. Our results suggest that market integration has evolved progressively. Over the past three decades, Hong Kong has gradually become a means for international investors to access Chinese assets. The Stock Connect Scheme is an innovative move with significant impacts to both Hong Kong and mainland stock markets. Policy makers lay out a broad strategy of market-oriented reform but in a manner that is controllable and expandable for cross-border Renminbi (RMB) flow by connecting Mainland market to international investors. It paves the way and is a natural consequence of steps that China is taking to open-up its capital account and facilitate the move towards RMB internationalization, which is critical both to the political and economic developments of China. The design of the Stock Connect Scheme provides a sustainable and scalable model for further expansion to world's major stock markets. Therefore, it is unsurprising to see the correlation of market capitalization occurring before the introduction of the Stock Connect Scheme as a positive development resulting from a wider investor base. It is also perhaps not that surprising to see the non-stationary observation of market index performance before the introduction of the scheme. This situation is reflected in the gradual growth of H-shares in the leading index constituents.

Further, as time has passed, the restrictions on accessing mainland markets have eased; thus, overseas investors can now access China's A-share market via a qualified quota known as QFII. Likewise, the introduction of RQFII in 2011 has allowed an investment outflow to international markets. In addition, higher levels of such co-movements are expected. Figures 2 and 3 show the growth of the QFII and RQFII quotas, respectively.

One of the obvious observations is that the weakening of the investment outflow from Hong Kong to China after the introduction of the Stock Connect Scheme also weakens Hong Kong's influence on China. While this study's tests generally agree on the evidence of linear causality for market capitalizations and the market indices before and after the introduction of the Stock Connect Scheme from China to Hong Kong, it is interesting to find nonlinear cases from 2015 onward that suggest a bilateral and possibly nonlinear degree of causal influence on each market. Heuristically, the speed of capital flow from one market to another and the difference in the H-share and A-share premium (see Figure 4) could drive the direction of funds. On the one hand, it is not difficult to see how Hong Kong has provided cheaper asset-buying opportunities in the past decade; on the other, the change in share premium difference between mainland China's domestic A-share markets and Hong Kong's H-share market could direct investors' appetites or sentiments. It is suggested here that these are aspects for further research in order to establish the type of nonlinear functional relationship and the dynamic drivers of such relationships.

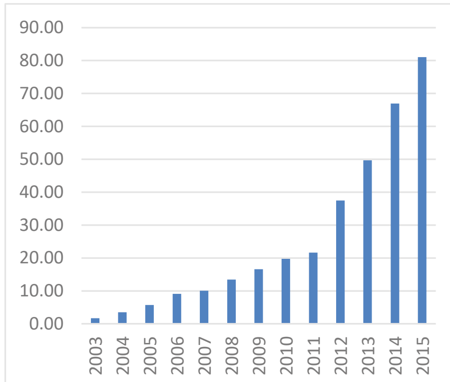

Figure 2. QFII Quota (**A** pprovals since 2003 (US$bn), Data source: SSE).

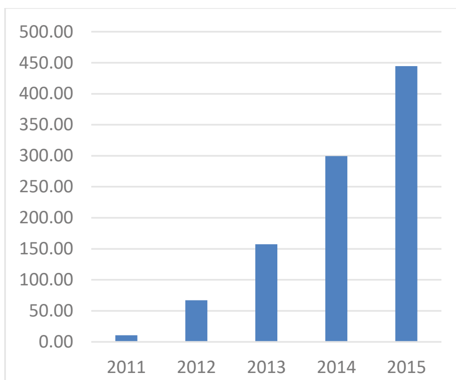

Figure 3. RQFII Quota (Approvals since 2011 (RMBbn), Data source: SSE).

Figure 4. The Hang Seng China AH Premium Index. (Data source. Bloomberg.)

This paper studies sustainability of financial integration among Shenzhen, Shanghai, and Hong Kong stock markets. An extension of our paper could study sustainability of other aspects of financial markets, for example, sustainability in warrant markets [48], sustainability in REITs [49], sustainability in equity return dispersion and stock market volatility [50], sustainability in herding behaviour [51], sustainability in portfolio selection [52], and sustainability in credit risk [53].

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Macroeconomic Shocks and Changing Dynamics of the U.S. REITs Sector

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Abstract: Unlike the existing literature, which primarily studies the impact of only monetary policy shocks on real estate investment trusts (REITs), this paper develops a change-point vector autoregressive (VAR) model and then analyzes, for the first time, regime-specific impact of demand, supply, monetary policy, and spread yield shocks, identified using sign-restrictions, on US REITs returns. The model first isolates four major macroeconomic regimes in the US since the 1970s and discloses important changes to the statistical properties of REITs returns and its responses to the identified shocks. A variance decomposition analysis revealed aggregate supply shocks to have dominated in the early part of the sample period, and monetary policy and spread shocks at the end. Our results imply that ignoring other possible shocks in the model is likely to lead to incorrect inferences, and over-reliance on (conventional) monetary policy in correcting for possible bubbles in the REITs sector, which it will fail to rectify, given the importance of other shocks driving the REITs sector.

Keywords: change-point VAR model; macroeconomic shocks; US REITs sector

1. Introduction

The rapid decline in real estate prices, following a prolonged boom, is commonly associated as the main underlying reason for the global economic and financial crisis of 2008 to 2009 [1,2]. Naturally, understanding what macroeconomic and financial shocks drives the real estate market is of paramount importance, especially for a policymaker aiming to avoid future catastrophic effects observed under the 'Great Recession'. While there exists a large number of studies that have analyzed the role of both conventional and unconventional (in the wake of the zero lower bound (ZLB) scenario) monetary policy [3–8], and more recently, fiscal policy shocks on real estate markets [9,10], and the feedback from it in shaping policy decisions, there is dearth of studies that have analyzed the role of aggregate demand, aggregate supply, and bond yield spread shocks on real estate markets. The only exception to this is the recent paper by Plakandaras et al. [11], where the authors study the effect of macroeconomic shocks in the determination of house prices in the US and the UK by employing time-varying parameter vector autoregressive (TVP-VAR) models covering the historical annual periods of 1830 to 2016 and 1845 to 2016, respectively. From the examination of the impulse responses of house prices on macroeconomic shocks, Plakandaras et al. [11], found that technology shocks dominate in the U.S. real estate market, while their effect is unimportant in the U.K, where, monetary policy shocks drives most of the house price evolution.

Against this backdrop, realizing that housing markets are regional in nature, with tremendous heterogeneity in terms of their response to (monetary) policy shocks [12–14], we analyze the role of various macroeconomic shocks in driving the Real Estate Investment Trusts (REITs) prices of the US, which tends to be homogenous across the country, being based on a broad single index. For our purpose, unlike Plakandaras et al. [11], we use higher-frequency (monthly) data covering the more recent period 1972:12 of 2016:12. The use of monthly data allows us to identify the shocks in a relatively cleaner manner [15,16], based on a change-point vector autoregressive (VAR) model that allows for different regimes throughout the sample period and identifies a variety of shocks (supply, demand, monetary policy, and the spread between long- and short-run maturities), derived from the theoretical reactions of an innovative general equilibrium model developed by Liu et al. [17]. This approach enables the VAR model to endogenously identify changes to the structure of the real estate market, as widely discussed in Simo-Kengne et al. [18], as well as variations to the properties of exogenous shocks during the sample period. We prefer to use this approach over the complete TVP-VAR framework used by Plakandaras et al. [11], as we want to explicitly identify regimes over our high-frequency data, rather than assuming that each point in time is a separate regime, as done in TVP-VARs—which is, perhaps, more appropriate at lower frequency data (like quarterly and annual). It is important to note that the spread shock is important for us, since the time period of our analysis involves the period of ZLB and hence, that of unconventional monetary policy, which in turn involved compression in the long-term yield spread (Beginning in the summer of 2007, money markets around the world experienced sustained periods of dysfunction with sharply higher short-term interest rates for commercial paper and interbank borrowing. This intense liquidity squeeze led the Federal Reserve (Fed) to substantially lower its Federal funds rate (FFR) and act as the liquidity provider of last resort to supply funds to banks and the broader financial system via its Term Auction Facility (TAF). The FFR, the Fed's traditional policy instrument, reached its effective ZLB in December 2008, and the Fed faced the challenge of how to further ease the stance of monetary policy as the economic outlook deteriorated. While the FFR had reached its effective ZLB, large-scale asset purchases (LSAPs), which reduced the supply of riskier long term assets and increased the supply of safer liquid assets (bank reserve), causing the spread to decline.). To the best of our knowledge, this is the first attempt to analyze the role of various macroeconomic and financial shocks over and above the monetary policy shock, in driving the REITs prices based on a change-point VAR. In this regard, it must be mentioned that the role of macroeconomic news surprises, along with monetary policy surprises for real estate markets have been recently studied by Marfatia et al. [19] and Nyakabawo et al. [20], based on single-equation approaches. However, these studies do not make an attempt to identify these shocks in a structural fashion based on a VAR model, and hence, cannot track the impact of these shocks over time, but just its correlation with the real estate returns (and volatility).

To summarize, given the importance of the real estate sector in the recent financial crisis, it is important to study the role of macroeconomic shocks driving the sector. However, existing studies have primarily concentrated on the role of monetary policy shocks and, in this regard, we deviate from the current literature by developing a change-point VAR model and then analyzing, for the first time, regime-specific impact of demand, supply, monetary policy, and spread yield shocks, identified using sign-restrictions, on US REITs returns. As indicated, based on our analysis over the monthly period of 1972:12 to 2016:12, aggregate supply shocks have dominated in the early part of the sample period, and monetary policy and spread shocks at the end. Our results imply that ignoring other possible shocks in the model is likely to lead to incorrect inferences, and over-reliance on (conventional) monetary policy in correcting for possible bubbles in the REITs sector, which it will fail to rectify, given the importance of other shocks driving the REITs sector. The remainder of the paper is organized as follows: Section 2 presents the data and the methodology, with Section 3 discussing the results, and Section 4 concluding the paper.

2. Data and Methodology

2.1. Sign Restrictions and Data

In this model, according to Kapetanios et al. [21] and Liu et al. [17], we investigated the four structural shocks: The monetary policy shock, the spread shock, the demand shock, and the supply shock and six variables: The short-term nominal interest rate (I_t), the REITs returns (R_t), the unemployment rate (U_t), the money holdings (M_t), the price inflation (π_t), and the interest rate spread S_t. We imposed the sign restrictions on the first period reaction of the VAR model and set the nominal interest rate such that it did not react to shocks during the financials crisis. The sign restrictions are presented in Table 1.

Table 1. Sign restrictions.

Shock\Variables	I_t	R_t	U_t	M_t	π_t	S_t
Monetary policy shock	$\geq$	$\leq$	$\geq$	$\leq$	$\leq$	$\leq$
Spread shock	$\leq$	$\geq$	$\geq$	$\geq$	$\leq$	$\leq$
Demand shock	$\geq$	$\geq$	$\leq$	$\leq$	$\geq$	$\geq$
Supply shock	$\geq$	$\geq$	$\leq$	?	$\leq$	$\leq$

Note: The sign '≥' denotes a positive response, the sign '≤' denotes a negative response, and '?' denotes an uncertain response that the sign can either be positive or negative, decided by the calibration of the model.

To derive the sign restrictions to impose on the change-point VAR model, we used the results derived from the New Keynesian Dynamic Stochastic General Equilibrium (NKDSGE) model of Liu et al. [17] to determine how each variable reacts to shocks. In the aftermath of a positive monetary policy shock, the real money holdings fall due to the higher cost of holding money. The increase in the nominal interest rate leads to a rise in the demand for short-term bonds that generates a fall in real activity and REITs prices and a rise in unemployment. The fall in output generates an increase in the long-run nominal interest rate, which is lower than the increase in the short-run interest rate, and hence the spread between long- and short-run interest rates falls. A positive interest rate spread shock increases the long-run interest rate, which generates a fall in consumption and output, as implied by the demand for long-term bonds. The contraction in output induces REITs prices to fall and unemployment to rise. The fall in output generates a reduction in inflation, as implied by the Phillips curve, whose effect is to induce a fall in the short-run interest rate (through the Taylor rule), which causes real money holdings to increase since the money demand is negatively related to the short-run nominal interest rate. The direct effect of the demand shock is to increase real activity and REITs prices with unemployment falling, since this shock actually increases the marginal utility of consumption for any given level of consumption, which in turn also increases the long-term nominal interest rate sharply due to the demand for long-term bond. The rise in output growth generates an increase in inflation, whose effect is to increase the short-term nominal interest rate, causing real money holdings to fall. The spread increases, since the increase in the long-term interest rate is stronger than the corresponding short-term interest rate increase. Finally, the aggregate supply shock produces an increase (decrease) in output (inflation), which results in increases in REITs prices and a decrease in unemployment. Output growth rises sharply and, therefore, induces the central bank to raise the short-term nominal interest rate, which generates a fall in the interest rate spread, and possibly also real money balances, with the final effect on the latter uncertain due to the positive income effect.

We collected data for the effective FFR, 10-Year Treasury bond yield at constant maturity, civilian unemployment rate, consumer price index (CPI), M2 definition of the money supply, and the monthly total returns index for the FTSE Nareit U.S. ALL REITs. The ALL REITs index is a market capitalization-weighted index that includes all tax-qualified REITs listed on the New York Stock Exchange, the American Stock Exchange, or the NASDAQ National Market List. We took data from the FRED database of the Federal Reserve Bank of St. Louis for all variables, barring the REITs index, which, in turn, was obtained from www.reit.com. Our sample covers the monthly period from 1972:12 to

2016:12, with the starting date driven by data availability at the time of writing this paper. We note that the end date is in line with one year from the end of the unconventional monetary policy regime, given that it is widely-believed that monetary policy takes over a year to affect the macroeconomic variables. In addition, the end date is also aligned with tapering of policies aimed towards stimulating the real estate market directly. The unemployment rate, CPI, and M2 were seasonally adjusted. The interest rate spread is defined as the 10-year yield minus the FFR. We used the 12-month percentage change to compute inflation, the growth rate of M2, and the growth rate of REITs prices.

2.2. Change-Point VAR Model

The model used in this paper is based on the change-point VAR model developed by Chib [22,23]. The detailed description is as follows:

$$Z_t = C_s + \sum_{j=1}^{K} B_s Z_{t-j} + \theta_s^{\frac{1}{2}} \varepsilon_t \tag{1}$$

where B_s and θ_s are the autoregressive coefficients depended on the regime and reduced form variance covariance matrices, the state variable s is modeled as a discrete time and follow an M state Markov chain with the transition probability matrix, and the transition probability matrix specifies s to be either stay at the current value or switch to the next higher value, but not allow to switch back to past regimes. The restricted transition probabilities matrix P is a diagonal matrix with the diagonal elements

$$p_{ij} = p(S_t = j \big| S_{t-1} = i) \tag{2}$$

where

$$p_{ij} > 0 \; if \; j = i + 1 \text{ or } i = j$$

$$p_{MM} = 1$$

$$p_{ij} = 0 \text{ otherwise.}$$

And in this paper, according to Liu et al. [17], it is suitable for us to set $M = 3$. The readers can refer to Chib [22,23] and Liu et al. [17] for more details. Thus, the restricted transition probability matrix is denoted by

$$\widetilde{P} = \begin{pmatrix} p_{11} & 0 & 0 & 0 \\ 1 - p_{11} & p_{22} & 0 & 0 \\ 0 & 1 - p_{22} & p_{33} & 0 \\ 0 & 0 & 1 - p_{33} & 1 \end{pmatrix} \tag{3}$$

2.3. Setting Dummy Observations

Based on the literature [17,24–26], we constructed the following matrices of dummy observations:

$$Y_D = \begin{pmatrix} \frac{diag(\gamma_1 \sigma_1 \cdots \gamma_N \sigma_N)}{\tau} \\ 0_{N \times (P-1) \times N} \\ \cdots \\ diag(\sigma_1 \cdots \sigma_N) \\ \cdots \\ 0_{1 \times N} \end{pmatrix} \text{ and } X_D = \begin{pmatrix} \frac{J_P \otimes diag(\gamma_1 \sigma_1 \cdots \gamma_N \sigma_N)}{\tau} & 0_{NP \times 1} \\ 0_{N \times NP} & 0_{N \times 1} \\ \cdots & \cdots \\ 0_{1 \times NP} & c \end{pmatrix} \tag{4}$$

where the matrix J_P stands for $diag(1, 2, \cdots, P)$, $\tau = 0.03$, and $c = 1$ standing for the tightness of the prior on the VAR coefficients and the constant terms, respectively [25]. We obtain the estimates of both σ_i and γ_i from the AR(1) model via Ordinary Least Squares (OLS) for $i = 1, 2, \cdots, N$, where σ_i stands for the standard deviation of the residual and γ_i is the estimate of the AR(1) coefficient.

2.4. Priors for VARs

We assume the priors of the coefficients to follow a normal distribution and the covariances to follow an inverted Wishart distribution, with the first M regimes assumed to follow a Normal Inverse Wishart prior [27,28]. The traditional approach is to assume that the priors of the coefficients follow the Multivariate Gaussian distribution with the vector zero mean and the covariance matrix with $diag(1000, 1000, \cdots, 1000)$. Howevwe, in this paper, to be consistent with the unconventional monetary policy regime and to ensure the lagged coefficients on the non-dependent variables in the interest rate equation are close to zero, we imposed the prior of the coefficients in this period to follow Multivariate Gaussian distribution with zero mean. In addition, the covariance matrix with the diagonal elements corresponding to the coefficients of interest in the interest rate equation was set to the value of 1×10^{-12}, and the remaining diagonal elements were set to be 1000, and other elements were set to zero.

2.5. Priors for the Transition Probability

We assume the priors for the nonzero elements of the transition matrix p_{ij} follow the Dirichlet distribution, namely $p_{ij}^0 = D\big(u_{ij}\big)$, where $D(\cdot)$ denotes the Dirichlet distribution and

$$u_{ij} = \begin{cases} 10 \; i = j \\ 1 \; i \neq j \end{cases} \tag{5}$$

In this model setting, one could easily show that the posterior distribution follows the Dirichlet distribution:

$$p_{ij} = D\big(u_{ij} + \pi_{ij}\big) \tag{6}$$

where π_{ij} denotes the times of regime i that is followed by regime j.

In addition, we tool the sample by using the Gibbs sampling algorithm, estimate the change-point VAR model with the 200,000 replications, and deleted the first 195,000 replications so that the remaining replications became more random. Readers can refer to Chib [22,23], Kim and Nelson [29] and Liu et al. [17] for more details.

3. Empirical Results

Figure 1 shows the estimated probability of the four regimes, with them corresponding to the periods of June 1973 to January 1985, February 1985 to January 2009, February 2009 to May 2013, and June 2013 to December 2016. The VAR model was estimated based on six lags, as suggested by the Bayesian Information Criterion (BIC), and hence the first regime starts from June, 1972. The estimate for the first breakpoint is consistent with financial liberalization in the US, with the second one corresponding to the end of the global financial crisis, and the third one with the 'tapering' of the unconventional monetary policies.

To tie these breakpoints to changing macroeconomic dynamics, Figure 2 plots some key reduced form summary statistics from the change-point VAR. The top panel of Figure 2 presents the persistence of each of the endogenous variables in the change-point VAR for each regime. The FFR, bond yield spread, and M2 growth performed very similarly throughout the sample period. These variables increased from regime 1 to regime 2 and decreased during regime 3, and then increased in regime 4. Moreover, the unemployment rate showed a similar trend in the first three regimes. The persistence of inflation and REITs return changed over all four regimes, and during the financial crisis, the persistence of inflation reached its lowest value, while the persistence of REITs returns reached its highest value.

The second panel of Figure 2 shows the diagonal elements of the error covariance matrix in each regime. We observed that the volatility of the reduced-form errors declined for all the time series, with a different extent from regime 1 to regime 2. Furthermore, during the last two regimes covering the financial crisis and unconventional monetary policies due to the ZLB, the volatility of the reduced-form errors increased for all the variables, except for the bond yield spread and the FFR.

The last panel of Figure 2 shows the unconditional volatility of each variable in each regime. The volatility of the bond yield spread, and CPI inflation were extremely similar throughout the whole sample period. In general, all the plots were consistent to the second panel, except the behavior of the CPI inflation in regime 3.

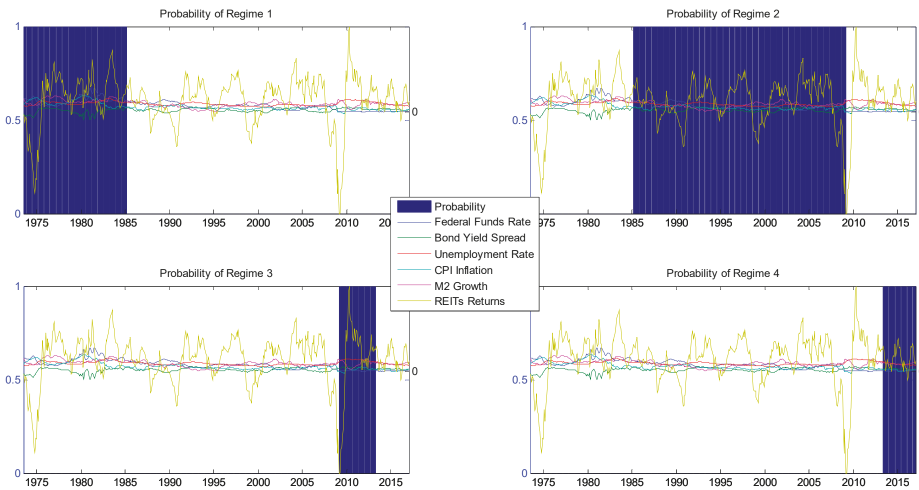

Figure 1. The estimated probability of each regime. Notes: The four regimes correspond to the periods June 1973 to January 1985, February 1985 to January 2009, February 2009 to May 2013, and June 2013 to December 2016.

The empirical framework is well-suited to investigate changes in macroeconomic dynamics across the sample horizon, since the change-point VAR model allows the coefficients in the model to vary across regimes. Figures 3–6 plot the impulse response functions (IRFs) of the six endogenous variables to a one-standard-deviation shock for the four identified shocks across the four regimes. We obtained the median and 68% confidence bands based on 5000 retained Gibbs replications. Since our focus is the REITs returns, we concentrate on discussing the effect of the various shocks on this variable. The effects on the other variables for the four shocks were similar to those obtained by Liu et al. [17], and the reader can refer to that paper for a more detailed discussion.

Figure 3 presents the responses of the variables to a contractionary monetary policy shock (i.e., an increase in the nominal interest rate). For the third regime, this shock was absent since the nominal interest rate was set at approximately zero, corresponding to the ZLB scenario. The size of the negative impact was quite similar in regimes 1 and 2, though it was relatively stronger under regime 1, with the effect being significant for about a year. The recovery was faster in regime 1 relative to regime 2, though the effect in the former regime increased again from three-years onwards. However, the strongest negative effect was observed in regime 4, with the effect being significant for over one and half years. This strong impact is probably an indication of the recovery that took place in the US real estate sector, and the economy in general, post the 'Great Recession'. In all cases, however, the effect on REITs returns was negative over the entire horizons of the 50 months considered.

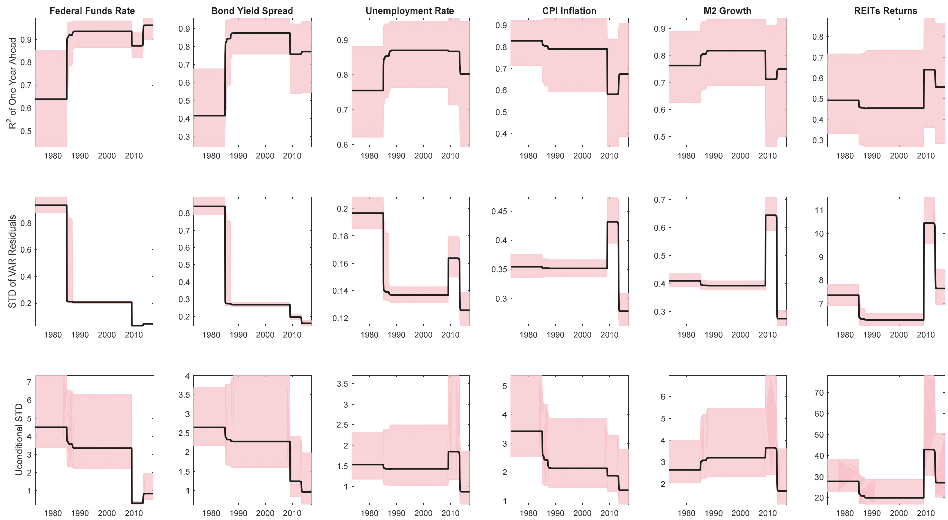

Figure 2. Regime dependent summary statistics; Note: See Notes to Figure 1.

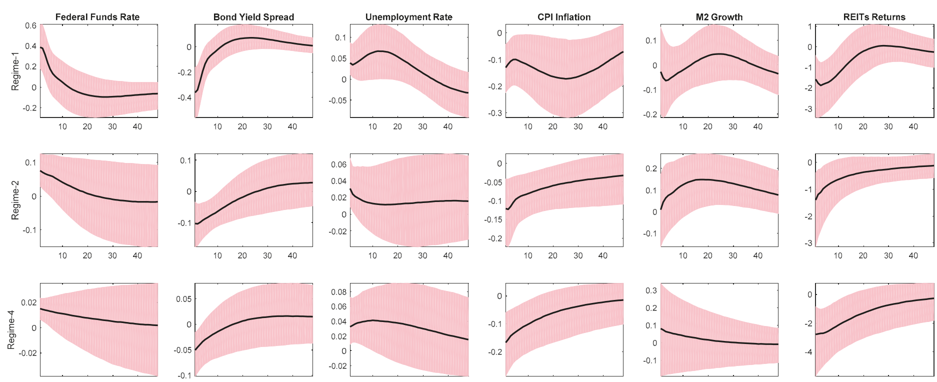

Figure 3. Impulse response functions to a contractionary monetary policy shock; Note: See Notes to Figure 1.

Next, Figure 4 presents the responses of the variables to a negative interest rate spread shock. To implement the analysis, we made it so that the short-term interest rate was exogenous to the spread shock in the third regime. Unsurprisingly, the positive impact on REITs returns tended to increase both in magnitude and length of the periods for which the effect was significant as we move from regimes 1 to 4. These results highlight the enhanced role of unconventional monetary policies in the third and fourth regimes aiming to reduce borrowing costs, as well as attempts made to directly stimulate the real estate sector, especially in the last identified sub-sample.

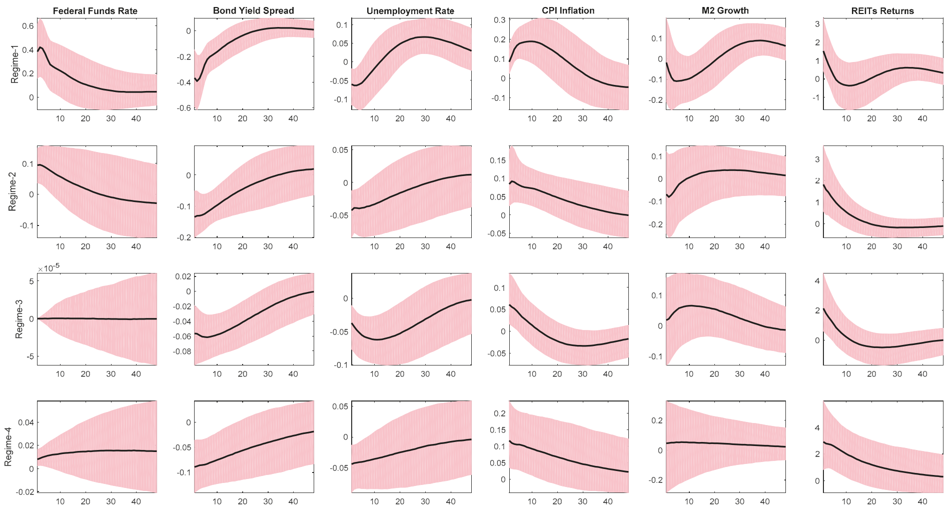

Figure 4. Impulse response functions to a negative interest rate spread shock; Note: See Notes to Figure 1.

Figure 5 presents the responses of the variables to an expansionary demand shock. The positive impact of REITs returns continued to increase in magnitude over the regimes, with the statistical significance also lasting for a longer number of horizons, especially in the last regime (where the effect was significant for over a year). While in Figure 6, we can see that the aggregate supply shock tended to positively affect the REITs returns, with the strongest effects observed in regimes 1, 3, and 4, with the effect declining during regime 2, with the effect being statistically longest-lasting (for over a year) in regime 3, i.e., right after the depth of financial crisis.

In summary, looking across all these impulse responses suggests that the transmission mechanism of the different shocks on REITs returns changed across the four regimes. To understand the extent to which movements of REITs returns can be explained by each shock and how the contribution of shocks changed across regimes, Figure 7 highlights the forecast error variance decompositions of the six endogenous variables for each of the four shocks. Concentrating on REITs returns, we observed that, the policy shock played an important role in the last regime (compared to the first two regimes), explaining over 30% of the variation in REITs returns. The spread shock was found to have quite a strong impact on regimes 2 and 4, with it explaining over 30% of the fluctuations in the real estate returns. Demand shocks explain about 14% and 8% of the variations in REITs returns in regimes 3 and 1, respectively. But the importance of the aggregate supply shocks stand out in regimes 1 and 2, with it explaining over 50% and 40% of the variations in regimes 1 and 2, and over 20% and 10% of the fluctuations of the REITs returns in regimes 3 and 4, respectively. The importance of the supply shocks is in line with Plakandaras et al. [11]. Overall, while supply shocks have been shown to be important in the early part of the sample, the spread and monetary shocks seem to dominate towards the end of the sample period under consideration.

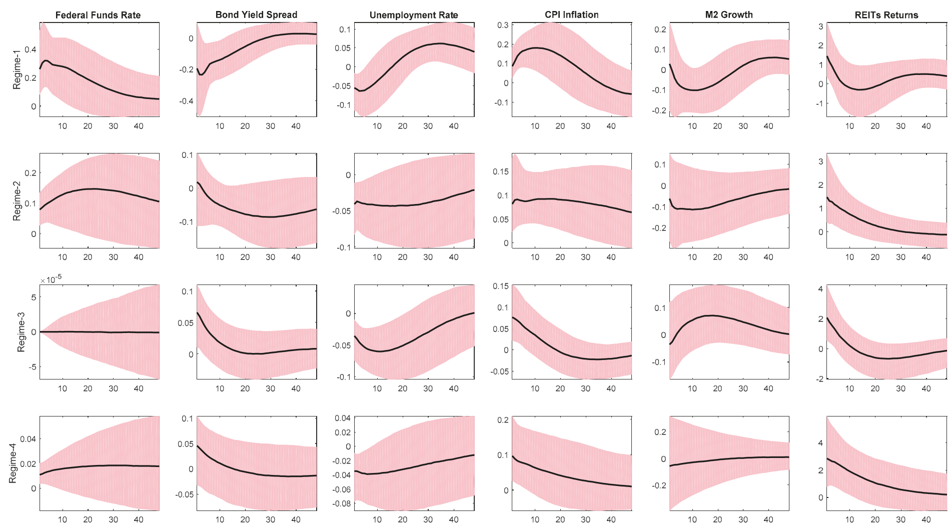

Figure 5. Impulse response functions to an expansionary demand shock; Note: See Notes to Figure 1.

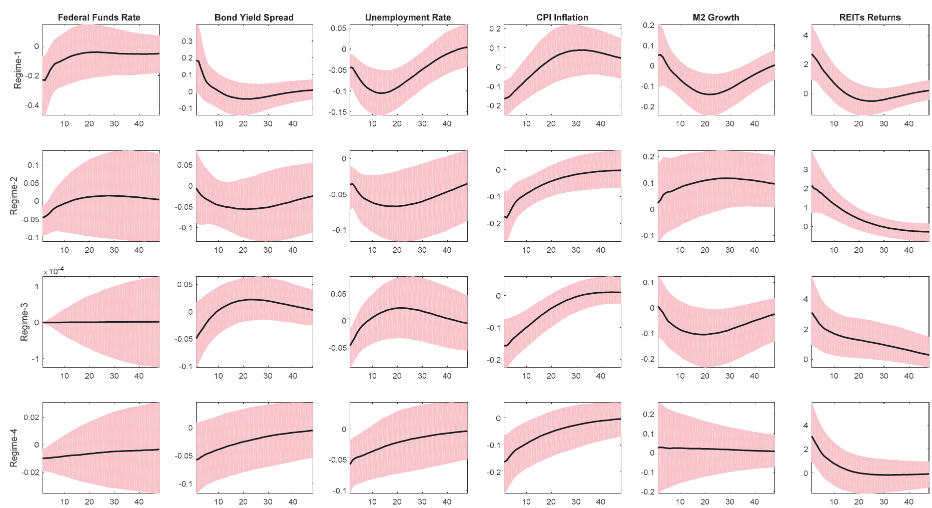

Figure 6. Impulse response functions to an expansionary supply shock; Notes: See Notes to Figure 1.

These results tend to suggest the importance of technical progress, i.e., the aggregate supply shocks, post-World War II in the US, which in turn led to a growth in productivity and hence output growth. This output growth is likely to have been driven by the consistently booming real estate market, until the collapse in 2007. The importance of the monetary policy and the spread shock in the last two regimes, basically coincided with the post-crisis period, where various measures of unconventional monetary policies were undertaken to boost the housing market and the overall macroeconomy. Our analysis thus indicates that while the role of monetary policy is important in driving the real estate sector of the US, it is also necessary to identify the role of other shocks, so that researchers do not overemphasize the role of monetary policy shocks.

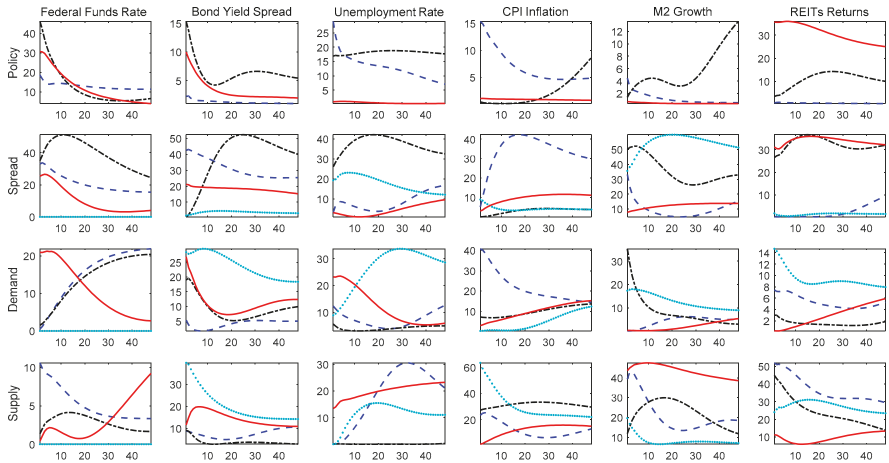

Figure 7. Forecast error variance decomposition; Notes: The four regimes correspond to the periods June 1973 to January 1985 (dashed blue line), February 1985 to January 2009 (dashed-dotted black line), February 2009 to May 2013 (dotted cyan line), and June 2013 to December 2016 (solid red line).

4. Conclusions

Given the importance of the real estate sector in causing the recent financial crisis, this paper uses a flexible change-point VAR model to analyze the regime-specific impact of various macroeconomic and financial shocks, identified based on sign-restrictions, on the US REITs returns. We deviate from the existing literature, which merely analyzes the role of monetary policy shocks on the US REITs sector and ignores the possible influence and importance of other shocks. The empirical model identifies three break points (four regimes) over the monthly sample period from 1972:12 to 2016:12. The third regime, coincides with the crisis period. The analysis discloses a range of important changes in the statistical and dynamic properties of REITs returns over the sample period. Statistical properties, such as persistence and volatility of fluctuations in REITs returns and the volatility of the reduced-form errors are found to have changed throughout the different regimes, with the crisis period being characterized by higher volatility. In addition, although quantitative changes are recorded throughout the whole period, supply, monetary policy, and spread shocks generate movements in REITs returns at the early and last parts of the sample period under consideration, respectively.

Hence, while the role of monetary policy is important in driving the real estate sector of the US, it is also necessary to identify the role of other shocks, in particular aggregate supply shocks to capture the role of productivity on the real estate sector, so that researchers do not overemphasize the role of monetary policy shocks. As we show, monetary policy shocks are only dominant in terms of moving the REITs sector post the recent financial crisis, in the wake of wide-array of unconventional monetary policy measures. This result also tends to suggest that, compared to productivity shocks, the role of monetary policy was minimal in heating up the US real estate market [30] before its collapse that led to the 'Great Recession'. Hence, loose monetary policy cannot be blamed for the real estate market bubble alone, though it is indeed true that post the financial liberalization in the US, the importance of monetary policy in affecting the real estate sector did increase [14].

From a policy perspective, our results have important implications. The relatively weaker role of conventional monetary policy, in affecting the REITs sector, tends to suggest that if there are bubbles in the US REITs sector, the Federal Reserve will not be successful in preventing it from bursting. In other words, besides the limited role of monetary policy on the REITs sector, the fact that interest rates are a blunt instrument to prick a bubble resulting in unintended collateral damage, the main policy message from our analysis is that the Federal Reserve should focus on stabilizing inflation and the output gap only—an observation in line with Bernanke and Gertler [31,32].

One limitation of this study is that we consider the overall REITs sector of the US. However, REITs data is available in a sector-specific manner involving equities and mortgages, which in turn could be affected differently from these shocks compared to the overall market. These possible dissimilarities could be studied as part of future research. Moreover, we ignore the role of fiscal policies in the paper, which also played an important role in the US macroeconomy, especially during the ZLB. In addition, our current study can be extended by analyzing REITs markets of other developed countries or regions like the UK, Euro Area, and Japan, which also faced a ZLB situation. Finally, our approach can also be applied to study the possible heterogenous impact of these shocks across the regional housing markets of the US.

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sustainability

MDPI

Article

Inclusive Financial Development and Multidimensional Poverty Reduction: An Empirical Assessment from Rural China

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Abstract: Inclusive finance is often considered to be a critical element that makes growth inclusive, as access to finance can enable the poor to lift themselves from income poverty. However, can it play such a role when the poor are in multidimensional poverty? Why does financial exclusion and poverty still exist in countries with vigorous development of inclusive finance? We build an evolutionary game model to analyze the equilibrium strategies of inclusive financial institutions and the poor in poverty reduction activities to find the answers. As there is a high incidence of poverty and serious financial exclusion in rural areas of China, we test the poverty reduction effectiveness of inclusive financial development on the poor with different labor capacity in rural China from 2010 to 2016 based on survey data of China Family Panel Studies and relevant statistics collected from 21 provinces. Our study finds there are differences in poverty alleviation effects of inclusive financial development among the poor with different labor capacities; if financial institutions target the service precisely to the working-age population in rural areas, they will achieve the dual goals of maintaining institutional sustainable development and alleviating poverty; And the development of inclusive finance in aspects of permeability, usability, and utility can significantly reduce multidimensional poverty. Therefore, to further improve the multidimensional poverty reduction performance and stimulate the endogenous motivation of the poor, it is necessary to strengthen the support for financial resources served to the working-age population, and to improve the development of rural inclusive finance in aspects of quality and affordability.

Keywords: inclusive finance; multidimensional poverty; targeted poverty reduction; evolutionary game; China

1. Introduction

To achieve the Millennium Development Goals on ending extreme poverty and hunger, the United Nations explicitly proposed to develop an inclusive financial system in 2005. The experience of Bangladesh's Grameen Bank, Bolivia's Banco Solidario, Indonesia's Bank Rakyat, rural Indonesia's Bank Kredit Desa and Latin America's Village Bank have confirmed that inclusive finance is an effective tool for achieving poverty alleviation and sustainable development [1]. In fact, poverty entails more than a lack of income and productive resources to ensure sustainable livelihoods. Its manifestations include hunger and malnutrition, limited access to education and other basic services, social discrimination and exclusion, as well as the lack of participation in insurance and decision-making. As multidimensional poverty is treated as matters of degree determined in terms of the individual's position in the distribution of some aspects of their living conditions and basic feasible capacity [2], we should use a new multidimensional method to measure poverty and analyze whether inclusive financial development can effectively alleviate multidimensional poverty, which helps countries gauge program effectiveness and guide their development strategy in a rapidly changing economic environment.

China is a developing country with a large number of rural poor. Ending poverty is also a major task for China to achieve sustainable development. Under the rural vitalization strategy, issues relating to agriculture, rural areas, and rural people are fundamental to China as they directly concern a country's stability and people's wellbeing. Therefore, the Chinese government has always adhered to the development-oriented poverty alleviation strategy and rural vitalization strategy. "Decision of the CPC Central Committee and the State Council on Winning the Fight against Poverty" was put forward, and the goal of poverty alleviation is to ensure that the rural poor will not worry about food and clothing anymore, and they will have the basic rights of compulsory education, basic medical treatment, and housing, in accordance with the policy of the United Nations on multidimensional poverty alleviation. Under the development-oriented poverty alleviation strategy, the method of poverty alleviation has shifted from "blood transfusion" to "blood creation"—poor people should depend on their own hard work to lift themselves out of poverty and get richer. However, the rural poor do not have enough money to strengthen nutrition, to improve welfare, or to develop production; worse, they are also excluded by formal financial sectors and cannot obtain the financial services they need. These factors lead to a vicious cycle [3]. In this case, inclusive finance can play a critical role in poverty alleviation, as increasing the rural poor's access to financial services at an affordable cost and with equal chance [4]. Access to a well-functioning financial system empowers the rural poor, can help them improve their livelihoods, protect them against economic shocks and provide funds for creating jobs or learning; in this way, developing inclusive finance targeted towards the poor in rural areas has become a key financial policy for China to promote inclusive economic growth.

However, inclusive finance does not alleviate poverty in the form of social assistance; it generally only addresses poverty issues with economic development prospects to maintain the sustainable development of its institutions, so its clients should have the potential for development and have the ability to repay the capital and interest [5]. Among the poor in rural areas, the group with the strongest labor capacity and development potential is the poor working-age population. They are also the key group for realizing the goal of "a people to work pull a family out of poverty". If a rural poor working-age population can improve its multidimensional poverty through access to the needed financial resources, the dual effect of promoting inclusive financial development and raising the level of human capital in rural areas can be achieved. As financial resources and labor resources are two essential factors for economic growth, it is also an important method for promoting the sustainable development of local economy [6]. Therefore, in the context of targeted poverty reduction and alleviation, can the development of inclusive finance achieve the goal of sustaining institutional sustainable development and achieving poverty alleviation? Are there any different poverty alleviation effects of inclusive financial development among the poor with different labor capacities? To better achieve poverty reduction targets, what is the developing direction of inclusive finance?

As there is a high incidence of poverty and serious financial exclusion in rural areas of China [7], we specialize in poverty alleviation effects of rural inclusive financial development under the rural vitalization strategy. Based on survey data of China Family Panel Studies (CFPS) and relevant statistics collected from 21 provinces, we measure poverty in a multidimensional method, studying the poverty reduction effects of rural inclusive financial development among the poor with different labor capacities, and analyze the difference of poverty reduction effects in different aspects of inclusive finance. Innovations are as follows: firstly, we analyzed the equilibrium strategies of inclusive financial institutions and the poor in poverty reduction activities from the perspective of the evolutionary game. Secondly, we analyzed the poverty alleviation effects of rural inclusive financial development on the rural poor with different labor capacities.

The remainder of this article is organized as follows. Section 2 reviews related literature, while Section 3 builds an evolutionary game model to analyze the action strategies of inclusive financial institutions and the poor in poverty reduction activities. Section 4 presents approaches to rural inclusive financial development measurement and multidimensional poverty measurement, and constructs the metrological model. Section 5 analyzes the empirical results, and Section 6 provides a conclusion and suggestions.

2. Literature Review

A lot of literature has studied the relationship between inclusive financial development and poverty alleviation. Some studies argue that (rural) inclusive financial development provides the poor with access to credit, savings, and other financial products and services, so that they can enjoy financial functions for poverty reduction directly. For instance, Kabeer found that microfinancial development in South Asia can and does make vital contributions to the economic productivity and social welfare of poor women and their households by financial empowerment [8]. Park and Mercado found that access to finance can enable the poor to make longer-term consumption and investment decisions, participate in productive activities, and cope with unexpected short-term shocks, which helps to alleviate poverty and income inequality [9]. Corrado and Corrado suggest that access to credit is a key instrument to access other primary services and social activities, so inclusive finance empowers the poor to exploit better economic and social opportunities and enable them to participate in productive economic activities [4]. He and Kong found that inclusive finance can increase poor farmers' income by the mechanism of releasing rural credit constraints, which helps them to improve the risk resistance ability and reduces the cost of obtaining financial services [10]. Some studies hold that (rural) inclusive financial development can further enhance the promotion of economic development and the optimization of income distribution in breadth, and indirectly achieve the results of income growth and poverty alleviation through the "trickle-down effect". Beck et al., Su and Liao, Ding, Cui and Sun, Chen and Zhang have verified this mechanism from the positive side by theoretical and empirical studies [11–15]. Leyshon and Thrift, Kempson and Whyley, Liu have verified this conclusion from the opposite side, finding that restraining financial development would increase the disparity of economic development and income distribution between regions, thus exacerbating the imbalance of regional economic development and resulting in more general social exclusion, which is not conductive to poverty alleviation [16–18]. Furthermore, some studies suggest that although inclusive finance can alleviate poverty and promote economic growth, it has different poverty reduction effects among different poor groups, the main beneficiaries being slightly poor families, and the effect of poverty reduction on extremely poor families being not significant [19]. Khaki and Sangmi found that access to finance can alleviate poverty, but funds are allocated to non-poor sections rather than absolute poor [20].Zhu and Wang showed that inclusive financial development can effectively alleviate poverty by promoting economic growth, but this effect is heterogeneous for different income groups, that is the benefit of poverty reduction and income increase of high-income rural poor is greater than that of low-income rural poor [21].

The literature above has studied the relationship between inclusive finance and poverty reduction from the point of view of different mechanisms, but ignores the premise that inclusive financial institutions are willing to provide financial products and services to the poor. Why does financial exclusion and poverty still exist in countries with vigorous development of inclusive finance? It maybe relates to the game between inclusive financial institutions and the poor. Based on the game model, some studies analyze the evolution process of cooperation between financial institutions and the poor. For example, Kong and Li deem that credit default leads to financial exclusion, and trust promotes cooperation [22]; Wang and Wang suggest that a bank's lending decision mainly depends on the possibility of farmers' repayment [23]. However, the poor need financial resources to enhance their production development ability to get out of poverty. Without considering malicious credit default, their repayment ability ultimately depends on the results of production development, which in turn depends on their labor ability. Therefore, there may be differences in poverty reduction between the working-age population and the non-working-age population.

In addition, the definition of poverty in current research is mainly limited to low income levels, and the effect of poverty alleviation is mainly judged by the income growth among all people. Moreover, the existing literature has not studied the poverty reduction effects of inclusive finance on the poor with different labor capacity, so the precision analysis of financial development for poverty alleviation is not enough. Based on this, an evolutionary game model is built to analyze the equilibrium strategies of inclusive financial institutions and the poor in poverty reduction activities, and we study the relationship between inclusive financial development and multidimensional poverty alleviation in rural areas of China.

3. An Evolutionary Game Model

As absolute poverty develops to relative poverty and social exclusion, it is more realistic to use multidimensional poverty to identify the poor. Multidimensional poverty mainly refers to the deficiency or deprivation of people's basic feasible capacity in many aspects, such as low income, ill health, inadequate education, lack of insurance, unemployment, and so on. Financial products and services help to enhance the self-development ability of the poor, so they need access to financial resources to alleviate poverty. However, the essence of inclusive finance is still finance, which is a commercial economic activity, and always refuses to provide products and services to the poor, especially the multidimensional poor, for the purposes of maintaining sustainable development. The poor have no mechanism to be lifted out of poverty. Therefore, financial institutions and the poor are stakeholders, and there is a game between them.

Suppose financial institutions and the poor are the two main players in the game of poverty reduction, and are both bounded rationality and limited information. To achieve the goal of poverty reduction, the poor need to obtain financial loans to carry out business activities. As a result, the poor have two strategies—one is to apply for loans, and the other is not to apply for loans. Although financial loans can help reduce multidimensional poverty, the poor may not be able to repay, which will affect the sustainable development of inclusive financial institutions. Therefore, financial institutions also have two strategies, accordingly—one is to provide loans and the other is not to provide loans. Suppose the probability of financial institutions providing loans is x and the probability of the poor applying for loans is y, then the probability of financial institutions not to providing loans is $1 - x$, and the probability of the poor not to applying for loans is $1 - y$. In addition, it is assumed that the loan amount is L, the interest rate is r, the investment rate of the loan is β, the transaction cost ratio of financial institutions providing loans is c_1, and the transaction cost ratio of the poor applying for loans is c_2, the success rate of developing production and management for the poor people is k. Under the condition that the poor apply for a loan, if the financial institutions provide the loan, then the return of the financial institution is $Lr - Lc_1$, the return of the poor is $k[L(\beta - r) - Lc_2] + (1 - k)(-Lc_2)$, if the financial institutions not to provide the loan, then the return of the financial institution is 0, the return of the poor is $k(-L\beta - Lc_2) + (1 - k)(-Lc_2)$. Under the condition that the poor not apply for a loan, if the financial institutions provide the loan, then the return of the financial institution is $-Lc_1$, the return of the poor is $-kL\beta$, if the financial institutions not to provide the loan, then the return of the financial institution is 0, the return of the poor is $-kL\beta$. The return matrix for financial institutions and the poor is shown in Table 1.

Table 1. The return matrix for financial institutions and the poor.

		The Poor	
		Apply	**Not to Apply**
Financial institutions	provide	$Lr - Lc_1$, $kL\beta - Lr - Lc_2$	$-Lc_1$, $-kL\beta$
	not to provide	0, $-kL\beta - Lc_2$	0, $-kL\beta$

As a result, the expected return on providing loans of financial institutions is $\pi_{11} = y(Lr - Lc_1) + (1-y)(-Lc_1) = yLr - Lc_1$. The expected return on not providing loans of financial institutions is $\pi_{12} = y \times 0 + (1-y) \times 0 = 0$. The average expected return of financial institutions is $\pi_1 = x\pi_{11} + (1-x)\pi_{12}$. Then the replicator dynamic model of financial institutions can be expressed as $F(x) = x(\pi_{11} - \pi_1) = x(1-x)(Lry - Lc_1)$. Make $F(x) = 0$, then $x_1 = 0, x_2 = 1, y^* = \frac{c_1}{r}$. The expected return on applying for loans of the poor is $\pi_{21} = x(kL\beta - Lr - Lc_2) + (1-x)(-kL\beta - Lc_2) = 2xkL\beta - xLr - kL\beta - Lc_2$. The expected return on not to applying for loans of the poor is $\pi_{22} = x(-kL\beta) + (1-x)(-kL\beta) = -kL\beta$. The average expected return of the poor is $\pi_2 = y\pi_{21} + (1-y)\pi_{22}$. Then the replicator dynamic model of the poor can be expressed as $F(y) = y(\pi_{21} - \pi_2) = y(1-y)[(2kL\beta - Lr)x - Lc_2]$. Make $F(y) = 0$, then $y_1 = 0, y_2 = 1, x^* = \frac{c_2}{2k\beta - r}$. Five equilibrium points of the evolutionary game can be obtained that are $(0,0), (0,1), (1,0), (1,1), (x^*, y^*)$.

However, the above five equilibrium points are local equilibrium points and not all of them are the equilibrium points of evolutionary stability strategy (ESS). Therefore, it is necessary to use a Jacobian matrix to verify the equilibrium points of ESS. Jacobian matrix can be obtained as shown in formula (1). If and only if the determinant value of the Jacobian matrix is greater than 0 and the trace value of the Jacobian matrix is less than 0, the equilibrium point of ESS can be obtained. Then the stability analysis results at each local equilibrium point are shown in Table 2.

$$J = \left\{ \begin{array}{cc} \frac{\partial F(x)}{\partial x} & \frac{\partial F(x)}{\partial y} \\ \frac{\partial F(y)}{\partial x} & \frac{\partial F(y)}{\partial y} \end{array} \right\} = \left\{ \begin{array}{cc} (1-2x)(Lry - Lc_1) & x(1-x)Lr \\ y(1-y)(2kL\beta - Lr) & (1-2y)[(2kL\beta - Lr)x - Lc_2] \end{array} \right\} \tag{1}$$

Table 2. The stability analysis results at each local equilibrium point.

Point	det(J)	Sign	tr(J)	Sign	Stability
$(0,0)$	$Lc_1 \times Lc_2$	+	$-Lc_1 - Lc_2$	-	ESS
$(0,1)$	$(Lr - Lc_1) \times Lc_2$	+	$(Lr - Lc_1) + Lc_2$	+	No
$(1,0)$	$Lc_1 \times (2kL\beta - Lr - Lc_2)$	+	$Lc_1 + (2kL\beta - Lr - Lc_2)$	+	No
$(1,1)$	$(Lc_1 - Lr) \times [-(2kL\beta - Lr - Lc_2)]$	+	$(Lc_1 - Lr) + [-(2kL\beta - Lr - Lc_2)]$	-	ESS
(x^*, y^*)	0		0		No

So $(0,0)$ and $(1,1)$ are the two equilibrium point of ESS. As obtaining loans helps poverty reduction, the equilibrium $(1,1)$ will be the optimal equilibrium point, i.e., the poor apply for loans and financial institutions provide the loan as the purpose of inclusive finance. However, the equilibrium of evolutionary game is not achieved overnight. Financial institutions and poor people will adjust the strategy of action according to their own return, and make the choice of strategy in a dynamic adjustment process. As the region consisting of points $(x^*, y^*), (0,1), (1,1)$ and $(1,0)$ will converge to $(1,1)$, and the region consisting of points $(x^*, y^*), (0,1), (0,0)$ and $(1,0)$ will converge to $(0,0)$, so if (x^*, y^*) is far from $(1,1)$, financial institutions and poor people will take the strategy (1,1). For the point $(x^*, y^*) = \left(\frac{c_2}{2k\beta - r}, \frac{c_1}{r}\right)$, when k is larger, the region consisting of points $(x^*, y^*), (0,1), (1,1)$ and $(1,0)$ will converge to $(1,1)$.

In practice, the stronger the labor capacity of the poor, the higher the success rate of their production and management. Since the poor working-age population with the strongest labor capacity and development potential, therefore, compared with the poor non-working-age population, if financial institutions provide loans to poor working-age population, they will achieve the dual goals of maintaining institutional sustainable development and alleviating poverty.

4. Variables and Models

4.1. Variables Measurement

4.1.1. China'sRural Inclusive Financial Development Index (CRIFI)

To reflect the development level of rural inclusive finance in China, it is necessary to construct an index system of rural inclusive financial development. At present, scholars have mainly measured the development level of inclusive finance from some perspectives of permeability, usability, utility, quality, and affordability—see Beck et al. [11], Sarma and Pais [24], Gupte et al. [25], Wang and Guan [26], Wu and Xiao [27], Chen et al. [28], Guo and Ding [29], Li et al. [30], Luo et al. [31], Zhang [32]—but their index system did not fully covered these five aspects above, and the inclusive development level studied by most of them is for the whole country rather than rural areas. Since the core of inclusive financial development is to enable more poor people and low-income people to enjoy equal access to financial services, and China's main battleground for poverty alleviation is in rural areas, especially in remote and the most difficult rural areas. Therefore, the development scope of inclusive finance in China is focused on the rural areas with the highest degree of financial exclusion and poverty in this article. Referring to the existing literature and combining it with the reality of rural financial development and the availability of rural financial data, we select the following indicators to construct the rural inclusive financial development index, as shown in Table 3. It should be noted that although internet finance and mobile finance are the new forms of inclusive finance and they have indeed greatly promoted the development of inclusive finance, considering they are mainly used in urban areas, the poor in rural areas are still largely excluded, so our index system does not include the related indicators.

Table 3. China's rural inclusive financial development index system.

Aspect	Index	Property
Permeability	Numbers of rural financial institutions per 10,000 square kilometers in rural areas [1]	positive
	Employees of rural financial institutions per 10,000 square kilometers in rural areas	positive
	Numbers of rural financial institutions per 10,000 people in rural areas	positive
	Employees of rural financial institutions per 10,000 people in rural areas	positive
Usability	Per capita deposit of rural population	positive
	Per capita loan of rural population	positive
Utility	Balance of deposits in rural financial institutions to primary industry added value [2]	positive
	Balance of loan in rural financial institutions to primary industry added value [2]	positive
Quality	Ratio of deposit to loan in rural financial institutions	negative
	Bad loan ratio of rural financial institutions [3]	negative
Affordability	Percentage of floating range of RMB loan interest rate	negative

[1] The rural financial institutions in this article include rural commercial banks, rural cooperative banks, rural credit cooperatives, village banks, rural loan companies, rural fund mutual aid cooperatives; Land area indicator is substituted by agricultural land area. [2] Limited by provincial data, the deposit balance and loan balance in this article are substituted by the deposit balance and loan balance of rural credit cooperatives. [3] In this article, the bad loan ratio of rural financial institutions in each province is obtained by the conversion of the bad loan ratio of the commercial banks in various provinces according to the ratio of bad loan between national rural commercial banks and national commercial banks.

As Beijing, Tianjin, and Shanghai are the developed regions of China, where the incidence of poverty is almost zero, we discard their rural inclusive financial development. Furthermore, although the incidence of poverty in Chongqing and Tibet are very high, these areas have also been excluded, as their statistical data are insufficient. Finally, taking into account the availability of data and the pertinence of the research, we use "Euclidean distance method" as formula (2), similar to Sarma and Pais [24], Wang and Guan [26] and Chen et al. [28], to calculate the development level of rural inclusive finance in 26 provinces of China from 2007 to 2016. Data is derived from the China Statistical Yearbook, the China Financial Yearbook, the Regional Financial Operation Report and the wind database. Partial calculation results are shown in Table 4.

$$\mathrm{CRIFI} = 1 - \frac{\sqrt{(w_{1t} - V_{1t})^2 + (w_{2t} - V_{2t})^2 + \cdots + (w_{mt} - V_{mt})^2}}{\sqrt{w_{1t}{}^2 + w_{2t}{}^2 + \cdots w_{mt}{}^2}} \tag{2}$$

Table 4. General situation of China's rural inclusive financial development from 2007 to 2016.

Region	Province	CRIFI	Rank	Permeability	Usability	Utility	Quality	Affordability
Eastern region	Guangdong	0.539	2	0.666	0.712	0.365	0.683	0.459
	Hebei	0.469	3	0.525	0.694	0.363	0.732	0.131
	Zhejiang	0.467	4	0.819	0.450	0.236	0.508	0.049
	Shandong	0.445	5	0.696	0.492	0.214	0.570	0.203
	Liaoning	0.364	7	0.495	0.558	0.163	0.501	0.372
	Jiangsu	0.321	9	0.761	0.102	0.044	0.647	0.268
	Fujian	0.258	14	0.308	0.391	0.133	0.639	0.216
	Hainan	0.237	16	0.291	0.446	0.086	0.749	0.663
	Average	0.388		0.570	0.480	0.200	0.629	0.295
Central region	Shanxi	0.622	1	0.508	0.837	1.000	0.450	0.303
	Henan	0.397	6	0.597	0.331	0.218	0.642	0.249
	Jiangxi	0.273	11	0.309	0.280	0.205	0.568	0.217
	Hunan	0.241	15	0.341	0.199	0.111	0.642	0.360
	Anhui	0.234	18	0.443	0.033	0.055	0.675	0.373
	Jilin	0.230	19	0.268	0.332	0.120	0.531	0.541
	Heilongjiang	0.184	22	0.170	0.382	0.121	0.483	0.371
	Hubei	0.179	24	0.278	0.091	0.042	0.701	0.652
	Average	0.295		0.364	0.311	0.234	0.586	0.383
Western region	Ningxia	0.324	8	0.226	0.534	0.388	0.610	0.260
	Shaanxi	0.320	10	0.249	0.528	0.342	0.640	0.497
	Guizhou	0.263	12	0.191	0.290	0.339	0.658	0.274
	Sichuan	0.259	13	0.253	0.341	0.223	0.468	0.275
	Yunnan	0.236	17	0.081	0.503	0.390	0.687	0.408
	Gansu	0.228	20	0.139	0.303	0.309	0.593	0.491
	Guangxi	0.222	21	0.200	0.325	0.176	0.710	0.474
	Inner Mongolia	0.181	23	0.105	0.563	0.161	0.574	0.190
	Xinjiang	0.151	25	0.044	0.448	0.176	0.573	0.747
	Qinghai	0.149	26	0.033	0.296	0.248	0.380	0.781
	Average	0.233		0.152	0.413	0.275	0.589	0.440

Data sources: Authors' calculations.

In formula (2), w_{mt} is the weight of index m in Table 1 in year t, which is determined by the coefficient of variation method as per Zhou et al. [6]. That is the ratio of the standard deviation to the average of the index in all provinces in each year. V_{mt} is the calculated value of index m in Table 1 in year t. That is, the data obtained by unifying the actual data and multiply it by the weight of index.

As shown in Table 4, there is a wide gap between regions in the development level of rural inclusive finance. The permeability, usability, and quality of rural inclusive financial development in eastern China are relatively high, but utility and affordability of inclusive financial development are relatively low. Therefore, in the eastern region it is necessary to further improve the use efficiency of the poverty alleviation funds and reduce the transaction costs of financial services. The development of inclusive finance in the central and western regions is relatively backward, so they should strengthen the development of all aspects of rural inclusive finance, in particular to further increase the coverage of financial institutions and support those in more rural poverty to have access to financial resources.

4.1.2. Multidimensional Poverty Index

At present, the research on multidimensional poverty mainly identifies the multidimensional poverty of households or farmers from the aspects of income, education, medical treatment, insurance, assets, and living standards, as per Wang and Alkire [33], Li [34], Zou and Fang [35], Alkire and Santos [36], Santos [37], Alkire and Seth [38], Zhang and Zhou [39], Guo and Zhou [40]. However, there is little research on individual multidimensional poverty, in which the index selection only includes income, health, education, and insurance dimensions, and does not emphasize the development of production or employment [41–43]. Since inclusive financial services are intended primarily for individuals rather than households, it is more effective and accurate to identify the poor from the individual level than from the family level. Furthermore, the existing literature only focuses on income, health, education, and insurance poverties, but neglects employment poverty. In fact, unemployment is also a crucial cause of individual poverty, which directly determines people's income level and social status [44]. Therefore, combined with factors affecting individual poverty, we calculate the multidimensional poverty of rural working-age population from five dimensions of income (economic capability), health (physical function), education (learning ability), insurance (risk-resisting ability) and employment (survival ability) by using the "dual cutoff method" of Alkire and Foster [45,46]. All dimensional indicators and deprivation cutoffs refer to the existing literature, the UN Millennium Development goals, Chinese poverty line, and the characteristics of survey data. There is equal weight for each indicator. Details are shown in Table 5.

Table 5. Five poverty dimensions and deprivation cutoffs.

Dimensions	Deprivation Cutoffs
Income	Income below the income poverty line 2300 RMB yuan (comparable prices based on year 2010) is regarded as "Income poverty".
Health	If body mass index (BMI) is outside the range of (18.5 kg/m^2, 30 kg/m^2)and self-rated health is unhealthy, that is regarded as "Health poverty".
Education	Failure to complete compulsory primary education (maximum length of education less than 6 years) is regarded as "Education poverty".
Insurance	Failure to enjoy any kind of endowment insurance or medical insurance is regarded as "Insurance poverty".
Employment	No job now and no formal work experience for more than six months is regarded as "Employ poverty" [1].

[1] Employment here includes do agricultural work and self-employment.

"Dual cutoff method" is also called "AF method", which uses deprivation cutoffs and poverty cutoffs to measure people's multidimensional poverty and was created by Alkire and Foster [45,46]. Assuming that the achievement level of ith individual in jth dimension is $y_{ij}(i = 1, 2, \cdots n; j = 1, 2, \cdots d)$, so an $(n \times d)$ data matrix Y is formed for n individuals and d dimensions. The row vector $y_{ij} = (y_{i1}, y_{i2}, \cdots y_{id})$ is the achievement level of each individual in a given dimension, and the column vector $y_{ij} = \left(y_{1j}, y_{2j}, \cdots y_{nj}\right)$ is the achievement level of each dimension for a given individual. A vector $z = (z_1, \cdots, z_d)$ of deprivation cutoffs is used to determine whether an individual is deprived. If y_{ij} falls short of the respective deprivation cutoff z_j, then this individual is said to be deprived in that dimension and considered to be poverty in that dimension; If y_{ij} is at least as great as the respective deprivation cutoff z_j, then this individual is not deprived in that dimension and not considered to be poverty in that dimension. The deprivation vector g^0_{ij} is used to represent an individual's deprivation. If ith individual is deprived in jth dimension,

$g_{ij} = 1$; if ith individual is not deprived in jth dimension, $g_{ij} = 0$. The deprivation vector of all individuals consists of a deprivation matrix $g^0 = \left[g_{ij}^0\right]$, which is composed of 0 and 1 elements. A column vector $c_{ij} = (c_{i1}, c_{i2}, \cdots c_{id})'$ of deprivation counts reflects the breadth of each individual's deprivation, so $c_{ij} = \sum g_{ij}$. A poverty cutoff k $(0 < k \leq d)$ is used to determine whether an individual is a multidimensional poverty people. If the deprivation counts c_{ij} falls short of the poverty cutoff k, the individual is not considered to be a multidimensional poverty people. In contrast, if the deprivation counts c_{ij} is at least as great as the poverty cutoff k, the individual is considered to be in multidimensional poverty. According to deprivation counts c_{ij}, n individuals and d dimensions, the value of multidimensional poverty M can be calculated, the formula is $M = \sum_1^n c_i(k)/nd$. The headcount ratio H is the proportion of multidimensional poverty people, if there are q multidimensional poverty peoples among n individuals, the headcount ratio H is calculated by q/n. The intensity A is the average deprivation share among the multidimensional poverty people, and it can be calculated by $\sum_1^n c_i(k)/qd$. The relationship between M, H and A is $M = H \times A$.

In this article, data of identifying multidimensional poverty population comes from the database of CFPS, which has been surveyed since 2010 for full sample data and each investigation lasts two years. To ensure the continuity and comparability of the samples, we select the survey data from 2010, 2012, 2014 and 2016, and only selects 21 provinces from 30 provinces that have been involved in the survey and rural inclusive financial development index have been calculated. Among the 30 provinces surveyed by CFPS, Inner Mongolia and Hainan Province were only included in the survey in 2014, and the valid samples were only 10 and 5, respectively. Qinghai were only included in the survey in 2012, and the valid samples were only 1. Ningxia and Xinjiang were included in the survey in 2012 and 2014, but their valid samples were only 6 and 19, respectively; Beijing, Tianjin, Shanghai, and Chongqing are dismissible for not calculating the rural inclusive financial development index. Thus, the nine provinces mentioned above are all excluded. In summary, the 21 provinces and regions are Hebei Province, Shanxi Province, Liaoning Province, Jilin Province, Heilongjiang Province, Jiangsu Province, Zhejiang Province, Anhui Province, Fujian Province, Jiangxi Province, Shandong Province, Henan Province, Hubei Province, Hunan Province, Guangdong Province, Guangxi Zhuang Autonomous region, Sichuan Province, Guizhou Province, Yunnan Province, Shaanxi Province, and Gansu Province. To ensure the validity of the sample, missing values and the abnormal values are deleted directly, and 20,094 valid samples are retained to calculate the multidimensional poverty of the rural population. Among them, there are 10,987 valid samples in 2010, 4582 valid samples in 2012, 3865 valid samples in 2014, and 660 valid samples in 2016. Partial calculation results are shown in Table 6. As shown in Table 6, the multidimensional poverty situation of rural population has improved as a whole, but the task of targeted poverty reduction and alleviation has not yet been completed; some rural populations still have problems of low income, ill health, inadequate education, lack of insurance, and unemployment. Health poverty and education poverty are the main poverty problems faced by them. It is necessary to continue to intensify efforts of poverty alleviation.

Table 6. Multidimensional poverty of rural population from 2010 to 2016.

Dimensions	Year	Poverty Status			Dimension Contribution Rate				
		M	H	A	Income	Health	Education	Insurance	Employ
One dimension	2010	0.212	0.626	0.336	0.251	0.208	0.311	0.109	0.121
	2012	0.126	0.452	0.274	0.178	0.370	0.354	0.021	0.077
	2014	0.175	0.516	0.334	0.241	0.275	0.244	0.069	0.171
	2016	0.174	0.593	0.292	0.085	0.243	0.298	0.209	0.165
	Avg	0.172	0.547	0.309	0.189	0.274	0.302	0.102	0.133
Two dimensions	2010	0.147	0.302	0.483	0.264	0.210	0.299	0.099	0.127
	2012	0.064	0.142	0.447	0.207	0.341	0.336	0.019	0.096
	2014	0.118	0.234	0.498	0.274	0.247	0.239	0.051	0.189
	2016	0.099	0.218	0.463	0.104	0.217	0.290	0.189	0.201
	Avg	0.107	0.224	0.473	0.212	0.254	0.291	0.090	0.153
Three dimensions	2010	0.069	0.106	0.644	0.265	0.225	0.275	0.092	0.143
	2012	0.020	0.034	0.603	0.258	0.329	0.305	0.027	0.081
	2014	0.061	0.090	0.667	0.273	0.253	0.232	0.027	0.215
	2016	0.032	0.049	0.640	0.123	0.241	0.235	0.212	0.189
	Avg	0.045	0.070	0.639	0.230	0.262	0.262	0.089	0.157
Four dimensions	2010	0.019	0.023	0.808	0.232	0.220	0.236	0.128	0.185
	2012	0.000	0.000	0.800	0.000	0.250	0.250	0.250	0.250
	2014	0.026	0.033	0.800	0.250	0.250	0.250	0.000	0.250
	2016	0.008	0.010	0.800	0.125	0.194	0.250	0.194	0.236
	Avg	0.013	0.017	0.802	0.152	0.229	0.246	0.143	0.230
Five dimensions	2010	0.001	0.001	0.000	0.200	0.200	0.200	0.200	0.200
	2012	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	2014	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	2016	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Avg	0.000	0.000	0.000	0.050	0.050	0.050	0.050	0.050

Data sources: Authors' calculations.

4.2. Model Selection and Variable Description

To test whether rural inclusive financial development can effectively reduce the multidimensional poverty of the rural population, this article constructs a benchmark regression model (3). In model (3), samples are divided into two groups: the working-age population and the non-working-age population.

$$\mathrm{MP_{it}} = \alpha_1 + \beta_1\mathrm{CRIFI_{it}} + \theta_1\mathrm{X_{it}} + \varepsilon_{it} \quad (3)$$

$\mathrm{MP_{it}}$ is the multidimensional poverty situation of the rural population, which describes whether the people are in multidimensional poverty on one of the five dimensions of income, health, education, insurance, and employment. If the rural population is in multidimensional poverty, $\mathrm{MP_{it}}$ takes 1, and if not, $\mathrm{MP_{it}}$ takes 0. In addition, $\mathrm{CRIFI_{it}}$ means Chinese rural inclusive financial development index, $\mathrm{X_{it}}$ is control variables, including personal characteristics variables such as gender, age, the square of age, household register, marital status, and family characteristics variables such as family size, family burden ratio, etc. ε_{it} is the random error. Since the explained variables in the benchmark regression model (3) are virtual variables, the panel Logit model is used for estimating. The main variable description is shown in Table 7.

Table 7. Variable description.

Variable	Description	N	Mean	St dev	Min	Max
MP_{it}	Poverty = 1 non-poverty = 0	20,094	0.559	0.497	0	1
CRIFI	continuous variable	20,094	0.356	0.130	0.136	0.653
crifi1	permeability	20,094	0.414	0.220	0.069	0.896
crifi2	usability	20,094	0.480	0.251	0	1
crifi3	utility	20,094	0.280	0.208	0	1
crifi4	quality	20,094	0.625	0.151	0.023	0.893
crifi5	affordability	20,094	0.311	0.191	0	1
gender	men = 1; women = 0	20,094	0.606	0.489	0	1
age	continuous variable	20,094	43.027	15.257	16	99
age2		20,094	2084.056	1403.238	256	9801
marriage	married = 0; others = 1 (Others include unmarried, cohabitation, divorce, widowhood.)	20,094	0.189	0.391	0	1
registration	rural household = 1; non-rural household = 0	20,094	0.915	0.279	0	1
family size		20,094	4.560	1.893	1	26
burden ratio		20,094	1.778	2.748	0.003	100
district	Eastern = 1; Central = 2; West = 3	20,094	1.992	0.839	1	3

5. Empirical Results

5.1. Benchmark Regression Results

According to the benchmark regression model (3), the influence coefficient and marginal effect of rural inclusive finance development on multidimensional poverty alleviation of rural population is shown in Table 8; columns (1), (3) are the influence coefficient, and columns (2), (4) are the marginal effect. From the empirical results, the p-value corresponding to all Wald statistics was 0.000, so model (3) passed the test as a whole. Then, it can be seen that the influence coefficient and marginal effect of rural inclusive finance on the multidimensional poverty of rural working-age population are significantly negative, but the influence coefficient and marginal effect of rural inclusive finance on the multidimensional poverty of rural non-working-age population are not significant. It suggests that in the case of other factors remaining unchanged, the development of rural inclusive finance will reduce the probability of rural working-age population falling into multidimensional poverty by 43.8%, but there is no significant impact of rural inclusive financial development on the poverty situation of rural non-working-age population. Therefore, compared with the poor non-working-age population, if financial institutions provide loans to poor working-age population, they will achieve the dual goals of maintaining institutional sustainable development and alleviating poverty. However, non-working-age population is less able to work, so the effect of inclusive finance on their poverty alleviation is not significant, which also proves the reason for there still existing financial exclusion to a small number of poor people.

In addition, from the empirical results we can also find that the influence coefficient and marginal effect of gender and the multidimensional poverty of rural population is significantly negative, which is shown by men being less likely to fall into multidimensional poverty than women in the case of other factors remaining unchanged. The relationship between age and the multidimensional poverty of the rural population is an "inverted U-shaped". The coefficient and marginal effect of marital status and the multidimensional poverty of rural population are significantly positive, indicating that the population in the marital status of unmarried, cohabiting, divorced, and widowed has a higher probability of falling into multidimensional poverty than those in the married state. The coefficient and marginal effect of household register and the multidimensional poverty of rural population is significantly positive, indicating that the population with a rural household register is more likely to fall into multidimensional poverty than those with a non-rural household register. Furthermore, the coefficient and marginal effect of family size and the multidimensional poverty of rural population is also negative. There is also a negative correlation between family burden ratio and multidimensional poverty of rural population. It shows that the rural population with lower family burden is more likely to get rid of poverty through hard work, and the rural population with higher family burden is more likely to fall into multidimensional poverty.

Table 8. Impact of rural inclusive financial development on multidimensional poverty.

	Benchmark Regression				Robustness Test			
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Working-Age		Non-Working Age		Working-Age		Non-Working Age	
CRIFI	−2.035 ***	−0.438 ***	−2.966	−0.318	−1.604 ***	−0.345 ***	−3.525	−0.378
	(0.632)	(0.136)	(2.405)	(0.258)	(0.528)	(0.113)	(2.251)	(0.241)
gender	−1.024 ***	−0.220 ***	−1.892 ***	−0.203 ***	−1.024 ***	−0.220 ***	−1.894 ***	−0.203 ***
	(0.036)	(0.007)	(0.198)	(0.020)	(0.036)	(0.007)	(0.198)	(0.020)
age	−0.104 ***	−0.022 ***	−0.948 **	−0.102 **	−0.104 ***	−0.022 ***	−0.956 **	−0.102 **
	(0.012)	(0.003)	(0.400)	(0.043)	(0.012)	(0.003)	(0.401)	(0.043)
age2	0.002 ***	0.000 ***	0.008 ***	0.001 ***	0.002 ***	0.000 ***	0.008 ***	0.001 ***
	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)
marriage	0.219 ***	0.047 ***	0.637 ***	0.068 ***	0.219 ***	0.047 ***	0.638 ***	0.068 ***
	(0.058)	(0.012)	(0.220)	(0.023)	(0.058)	(0.012)	(0.220)	(0.023)
registration	0.485 ***	0.104 ***	0.488 ***	0.052 ***	0.483 ***	0.104 ***	0.490 ***	0.052 ***
	(0.071)	(0.015)	(0.168)	(0.018)	(0.071)	(0.015)	(0.168)	(0.018)
family size	−0.017	−0.004	−0.035	−0.004	−0.017	−0.004	−0.035	−0.004
	(0.011)	(0.002)	(0.030)	(0.003)	(0.010)	(0.002)	(0.030)	(0.003)
burden ratio	−0.032 ***	−0.007 ***	−0.015	−0.002	−0.032 ***	−0.007 ***	−0.015	−0.002
	(0.011)	(0.002)	(0.022)	(0.002)	(0.011)	(0.002)	(0.022)	(0.002)
year	Y	Y	Y	Y	Y	Y	Y	Y
province	Y	Y	Y	Y	Y	Y	Y	Y
Intercept	2.412 ***	-	33.153 **	-	2.268 ***	-	33.842 **	-
	(0.391)	-	(13.671)	-	(0.369)	-	(13.696)	-
N	15,590	15,590	2603	2603	15,590	15,590	2603	2603
Quasi R2	0.106	0.106	0.177	0.177	0.106	0.106	0.178	0.178
Wald test	1928.38	-	255.34	-	1927.28	-	256.41	-
p-value	0.000	-	0.000	-	0.000	-	0.000	-

Note: The values in parentheses are standard deviations; *, **, *** indicate the level of significance of 10%, 5%, and 1%, respectively. Data is calculated by authors using Stata13.

5.2. Robustness Test

Based on Sarma and Pais [24], Sarma [47] improved the calculation method of the inclusive financial development index. In contrast to the calculation method of the normalized inverse Euclidian distance between the achievement point and the ideal point in the past, Sarma [47] uses a simple average of the normalized Euclidian distance between the achievement point and the worst point and the normalized inverse Euclidian distance between the achievement point and the ideal point as formula (4). Therefore, we use this new method to recalculate the CRIFI, and apply the modified index to the benchmark model (3). The results are unchanged as shown in Table 8.

$$\text{CRIFI} = \frac{1}{2}\left[\frac{\sqrt{(V_{1t})^2+(V_{2t})^2+\cdots+(V_{mt})^2}}{\sqrt{w_{1t}{}^2+w_{2t}{}^2+\cdots w_{mt}{}^2}} + \left(1 - \frac{\sqrt{(w_{1t}-V_{1t})^2+(w_{2t}-V_{2t})^2+\cdots+(w_{mt}-V_{mt})^2}}{\sqrt{w_{1t}{}^2+w_{2t}{}^2+\cdots w_{mt}{}^2}}\right)\right] \tag{4}$$

From the results of the robustness test we can also find that the influence coefficient and marginal effect of rural inclusive finance on the multidimensional poverty of rural working-age population are significantly negative, but the influence coefficient and marginal effect of rural inclusive finance on the multidimensional poverty of rural non-working-age population are not significant. It suggests our conclusion is robust.

5.3. Endogenous Test

As finance is an important method of development-oriented poverty alleviation, the Chinese government has issued several documents to support the financial sector in strengthening poverty alleviation, especially in areas with deep poverty, so multidimensional poverty of rural population may also affect the development of inclusive finance. Furthermore, there may be some endogenous problems in model setting, such as missing variables, which make the estimation result biased. Therefore, we select an index that lags two years behind the rural inclusive financial development as the instrumental variable, and use the Ivprobit model for a two-step method. The regression result is shown in Table 9. The result of Wald endogenous test shows that the model is endogenetic and the instrumental variable is highly correlated with the endogenous variable. However, the endogenous influence can be eliminated by Ivprobit model regression, and the regression result is consistent with the benchmark model.

Table 9. Endogenous test.

	Working-Age		Non-Working Age	
Variables	**First Step**	**Second Step**	**First Step**	**Second Step**
IFI		−2.423 ***		−0.697
		(0.618)		(1.943)
IFI2(instrumental variable)	0.610 ***		0.647 ***	
	(0.005)		(0.011)	
X_{it}	Y	Y	Y	Y
year	Y	Y	Y	Y
province	Y	Y	Y	Y
N	15,590	15,590	2603	2603
Wald test	6.24	6.24	0.45	0.45
P	0.013	0.013	0.5003	0.5003

Note: The values in parentheses are standard deviations; *** indicate the level of significance of 1%, respectively. Data is calculated by authors using Stata13.

5.4. Further analysis

The result of benchmark regression has proved that inclusive financial development can effectively alleviate the multidimensional poverty of the working-age population. In addition, to study which aspects of inclusive finance are more effective for poverty reduction of the working-age population, we study the poverty reduction effectiveness of permeability, usability, utility, quality, and affordability of inclusive finance based on model (3). The test result is shown in Table 10. We can see that the development of inclusive finance in aspects of permeability, usability, and utility can significantly reduce multidimensional poverty, but the development of inclusive finance in aspects of quality and affordability has no significant effect on the alleviation of multidimensional poverty. As the development of "permeability" is manifested in the expansion of the network coverage of financial institutions and the further sinking of financial services, which can extend the financial markets to more remote and poorer areas. The development of "usability" is manifested in the increased demand and participation of rural inclusive finance among rural poor people, so that more of them can have access to financial services without the restriction of mortgage conditions. The development of "utility" is manifested in the expansion of agricultural credit scale and the enhancement of the capacity to promote agricultural production and rural economic development, which is conducive to letting the poverty alleviation funds exert the maximum benefits, and truly achieve poverty alleviation and deliver genuine outcomes. Therefore, the development of rural inclusive finance can alleviate the multidimensional poverty of rural working-age population by improving the availability of financial products and services. However, the role of improving the quality of inclusive financial services and reducing the cost of services for poverty reduction has not yet been played, and the development of these two aspects should be further improved in the future.

Table 10. Impact of each aspect of rural inclusive financial development on multidimensional poverty.

	(1)	(2)	(3)	(4)	(5)
ifi1	−1.569 *				
	(0.801)				
ifi2		−0.392 **			
		(0.170)			
ifi3			−0.970 **		
			(0.378)		
ifi4				−0.079	
				(0.159)	
ifi5					0.178
					(0.130)
X_{it}	Y	Y	Y	Y	Y
year	Y	Y	Y	Y	Y
province	Y	Y	Y	Y	Y
_cons	2.324 ***	1.750 ***	1.761 ***	1.538 ***	1.453 ***
	(0.505)	(0.284)	(0.281)	(0.287)	(0.257)
N	15,590	15,590	15,590	15,590	15,590
r2_p	0.106	0.106	0.106	0.106	0.106

Note: The values in parentheses are standard deviations; *, **, *** indicate the level of significance of 10%, 5%, and 1%, respectively. Data is calculated by authors using Stata13.

6. Conclusions and Suggestion

Based on the evolutionary game model and empirical analysis, there are different poverty alleviation effects of inclusive financial development among the poor with different labor capacities. The development of China's rural inclusive finance can significantly alleviate the multidimensional poverty of rural working-age population, but this effect is not significant to the non-working-age population. Therefore, compared with the poor non-working-age population, if financial institutions provide loans to poor working-age population, they will achieve the dual goals of maintaining institutional sustainable development and alleviating poverty. In addition, the study also found that gender, age, marital status, household registration, family size and family burden ratio had significant effects on improving the multidimensional poverty of the rural population, and women are more likely to fall into multidimensional poverty than men, adults who are not married are more likely to fall into multidimensional poverty than those who are married, and the population with a rural household registration is more likely to fall into multidimensional poverty than those with a non-rural household registration, and the population with heavy family burden is more likely to fall into multidimensional poverty. Furthermore, the development of inclusive finance in aspects of permeability, usability, and utility can significantly reduce multidimensional poverty, but the development of inclusive finance in aspects of quality and affordability has not played its role on poverty alleviation.

Therefore, this article argues that in the game of poverty reduction, the stronger the labor capacity of the poor, the easier it is for the financial institutions and the poor to reach the equilibrium strategy of providing loans and applying for loans. So improving the financial availability of the working-age population is an effective way to fully realize the strategic goal of poverty alleviation in China. Furthermore, it even provides a new idea for poverty alleviation in the world. To further promote the development of rural inclusive finance, and guide rural inclusive finance to help target poverty alleviation, this paper puts forward the following policy suggestions. First, inclusive finance in poverty areas such as rural areas need to be developed, especially in remote and destitute rural areas. Second, rural areas, especially in the central and western regions, should speed up the development of the permeability, usability, and utility of inclusive finance. The quality and affordability of inclusive finance should be improved, especially in the east regions. Therefore, the eastern region should constantly innovate financial products and services, accelerate the development of internet finance and mobile finance, appropriately reduce transaction costs of financial services based on improving the quality of financial services, and effectively enable the poor to enjoy the benefits of inclusive financial development. The central and western regions should accelerate rural financial reforms, fully encourage and guide the policy-oriented financial institutions, commercial financial institutions, internet financial and mobile finance institutions to establish multi-level, wide-coverage, and sustainable rural inclusive financial systems in rural areas. Third, it is necessary to guide rural inclusive finance to give priority to serving the poor working-age population with the strongest ability to work and develop in rural areas, and constantly stimulate their endogenous motivation to lift themselves out of poverty through hard work, and improve their capacity for study and production. It is necessary to continuously improve the effectiveness and sustainability of alleviation effects of rural inclusive financial development on the multidimensional poverty of the rural working-age population.

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Size, Internationalization, and University Rankings: Evaluating and Predicting Times Higher Education (THE) Data for Japan

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Abstract: International and domestic rankings of academics, academic departments, faculties, schools and colleges, institutions of higher learning, states, regions, and countries are of academic and practical interest and importance to students, parents, academics, and private and public institutions. International and domestic rankings are typically based on arbitrary methodologies and criteria. Evaluating how the rankings might be sensitive to different factors, as well as forecasting how they might change over time, requires a statistical analysis of the factors that affect the rankings. Accurate data on rankings and the associated factors are essential for a valid statistical analysis. In this respect, the Times Higher Education (THE) World University Rankings represent one of the three leading and most influential annual sources of international university rankings. Using recently released data for a single country, namely Japan, the paper evaluates the effects of size (specifically, the number of full-time-equivalent (FTE) students, or FTE (Size)) and internationalization (specifically, the percentage of international students, or IntStud) on academic rankings using THE data for 2017 and 2018 on 258 national, public (that is, prefectural or city), and private universities. The results show that both size and internationalization are statistically significant in explaining rankings for all universities, as well as separately for private and non-private (that is, national and public) universities, in Japan for 2017 and 2018.

Keywords: international and domestic rankings; size; internationalization; national; public and private universities; changes over time

JEL Classification: C18; C81; I23; Y1

1. Introduction

It is well known that a broad range of higher-education rankings of academics, academic departments, faculties/schools/colleges, institutions of higher learning, states, regions, and countries are of academic and practical interest and importance to students, parents, academics, and private and public institutions. The international and domestic rankings are typically based on a variety of arbitrary methodologies and criteria, which means they are not optimal from a statistical perspective. Moreover, evaluating how the rankings might be sensitive to different factors, as well as forecasting how they might change over time, requires a statistical analysis of the wide variety of factors that affect the rankings.

The primary purpose of this paper was to evaluate and predict the relationships over time among rankings and two crucial factors. The three leading and most influential annual sources of international and domestic university rankings are as follows:

(1) Shanghai Ranking Consultancy Academic Ranking of World Universities (ARWU) (originally compiled and issued by Shanghai Jiao Tong University), founded in 2003;
(2) Times Higher Education (THE) World University Rankings, founded in 2010 (*THE–QS World University Ranking*, in partnership with QS, 2004–2009);
(3) Quacquarelli Symonds (QS) World University Rankings, founded in 2010 (*THE–QS World University Ranking*, in partnership with THE, 2004–2009).

ARWU was the first agency to rank world universities, and was followed closely by THE–QS, which used a different methodology. Since 2010, ARWU, THE, and QS used different methodologies, with each having their supporters and critics.

As stated succinctly by THE (2018) [1]:

"The Times Higher Education World University Rankings, founded in 2004, provide the definitive list of the world's best universities, evaluated across teaching, research, international outlook, reputation, and more. THE's data are trusted by governments and universities and are a vital resource for students, helping them choose where to study."

THE (2018) [1] recently provided the Young Universities Rankings, World Reputation Rankings, Emerging Economy Rankings, Japan University Rankings, Asia University Rankings, World University Rankings, United States (US) College Rankings, and, most recently, Latin America Rankings and Europe Teaching Rankings. These separate rankings provide a rich source of data for two countries, namely the USA and Japan (see THE (2018) [2] and THE (2018) [3], respectively, for further details), and alternative groupings of countries and regions (for Asia, see THE (2018) [4]) (https://www.timeshighereducation.com/world-university-rankings/2018/regional-ranking#!/page/0/length/25/sort_by/rank/sort_order/asc/cols/stats).

Institutions of higher learning in the US were analyzed extensively and comprehensively over an extended period. However, this was not the case in Japan, as data on a wide range of national, public, and private universities were not readily available. Recently, THE (2018) [5] provided data for Japan on numerical rankings for 258 national, public (that is, prefectural or city), and private universities.

THE (2018) [5] gives the following explanation of the dataset:

"The Times Higher Education Japan University Rankings 2018, based on 13 individual performance metrics, are designed to answer the questions that matter most to students and their families when making one of the most important decisions of their lives—who to trust with their education.

This year's methodology includes the same 11 indicators as last year, as well as two additional internationalization measures: the number of students in international exchange programs, and the number of courses taught in a language other than Japanese.

The rankings include the top-ranked 150 universities by overall score, as well as any other university that is in the top 150 for any of the four performance pillars (resources, engagement, outcomes, and environment). Scores in each pillar are provided when the university is in the top 150, while a dash ("–") indicates that the institution is not ranked in the top 150 for that pillar.

Institutions outside the top 150 are shown with a banded rank ("151+") and a banded score ("9.4–38.2": these two numbers represent the lowest and highest scores of all universities ranked outside the top 150), and are displayed in alphabetical order."

The dataset includes a number of factors that are used in defining the ranking, but they cannot be used to predict the rankings. For purposes of predicting rankings in advance of obtaining the data that are used to construct them, two factors that should have a significant effect on rankings will be used to evaluate and predict the effects of **size** (specifically, the number of full-time-equivalent (FTE) students, or **FTE** (**Size**)) and **internationalization** (specifically, the percentage of international students, or **IntStud**) on academic rankings of the private and non-private (that is, national and public) universities in Japan. Sources of whether universities are national, public, or private are given at the following websites, as well as on the respective university websites:

National:
http://www.mext.go.jp/en/about/relatedsites/title01/detail01/sdetail01/1375122.htm;
Public:
http://www.mext.go.jp/en/about/relatedsites/title01/detail01/sdetail01/1375124.htm;
Private:
http://www.mext.go.jp/en/about/relatedsites/title01/detail01/sdetail01/sdetail01/1375152.htm.

The analysis of the data on these three key variables will enable a statistical analysis of, and response to the following issues relating size and internationalization of non-private and private universities to their respective rankings over time:

(i). Are private or non-private universities more highly ranked?
(ii). Are private or non-private universities larger in terms of size?
(iii). Do private or non-private universities have a higher degree of internationalization?
(iv). Do the size, internationalization, and rankings of private and non-private universities change over time?
(v). Are there differences in the effects of size and internationalization on the rankings of private universities?
(vi). Are there differences in the effects of size and internationalization on the rankings of non-private universities?
(vii). Do the effects of size and internationalization change over time for private and non-private universities?

There is extensive literature on university rankings and, more generally, on methodologies used to generate such rankings. There are numerous studies relative to a number of industries that compared results from different methods, and approaches that emphasize the differences and similarities related to rankings, as highlighted below.

Carrico et al. (1997) [6] considered data envelope analysis and university selection. Hu et al. (2017) [7] analyzed a hybrid fuzzy DEA/AHP methodology for ranking units in a fuzzy environment. Dale and Krueger (2002) [8] estimated the payoff to attending a more selective college through an application of selection on observables and unobservables. Eccles (2002) [9] evaluated the use of university rankings in the United Kingdom. Federkeil (2002) [10] examined some aspects of ranking methodology of German universities. Kallio (1995) [11] considered the factors influencing the college choice decisions of graduate students. Liu et al. (2005) [12] commented on the "fatal attraction" of academic ranking of world universities using scientometrics. lo Storto (2016) [13] analyzed the ecological efficiency-based ranking of cities based on a combined DEA cross-efficiency and Shannon's entropy method. McDonough et al. (1998) [14] evaluated college rankings based on democratized college knowledge. Meredith (2004) [15] analyzed why universities compete in the ratings game with an empirical analysis of the effects of the US News and World Report College Rankings. Merisotis (2002) [16] examined the ranking of higher-education institutions. Pavan et al. (2006) [17] evaluated data mining by total ranking methods based on a case study on optimization of the "pulp and bleaching" process in the paper industry. Lastly, van Raan (2005) [18] examined the fatal attraction ranking of universities by bibliometric methods.

Additional research papers that examined international and domestic university rankings can be found in a wide range of international journals. Some recent papers based on scientific publishing, country-specific and industrial linkage factors, and the associated policy implications include Tijssen et al. (2016) [19], Piro and Sivertsen (2016) [20], Shehatta and Mahmood (2016) [21], Moed (2017) [22], Kivinenet al. (2017) [23], Pietrucha (2018) [24], and Johnes (2018) [25].

The remainder of the paper is organized as follows: Section 2 discusses the data and descriptive statistics, while the empirical analysis is presented in Section 3, and some concluding remarks are given in Section 4.

2. Data and Descriptive Statistics

As discussed in Section 1, in the dataset released in THE (2018d), cardinal rankings are given for the leading 100 and 101 universities in 2017 and 2018, respectively, with 50 universities listed in intervals from 101–110, 111–120, 121–130, 131–140, and 141–150. The remaining 108 universities are listed equally as 151+.

Table 1a,b show the universities that have more than 20% internationalization, where IntStud denotes the percentage of international students, in 2017 and 2018, respectively. The universities are essentially all private, with seven of seven and six of seven in Table 1a,b, respectively. The sole exception is Akita International University (AIU), a public (specifically, prefectural) university, in Table 1b. Ritsumeikan Asia Pacific University has the highest IntStud scores in both years, with 46.5% and 53.4%, in 2017 and 2018, respectively, as well as being ranked 24th and 21st in Japan in these two years. At 12, AIU has the highest ranking of the universities in the two tables, with all the other private universities being ranked in the range 151+.

Table 1. (**a**) More than 20% IntStud 2017. (**b**) More than 20% IntStud 2018.

University	Rank	Type	Prefecture	IntStud
		(**a**)		
Ritsumeikan Asia Pacific University (APU)	24	Private	Oita	46.50
Digital Hollywood University	151+	Private	Tokyo	35.10
Kobe International University	151+	Private	Hyogo	31.00
Tokyo Fuji University	151+	Private	Tokyo	30.60
Okayama Shoka University	151+	Private	Okayama	22.90
Tokuyama University	151+	Private	Yamaguchi	21.00
Hokuriku University	151+	Private	Ishikawa	20.40
		(**b**)		
Ritsumeikan Asia Pacific University (APU)	21	Private	Oita	53.40
Osaka University of Tourism	151+	Private	Osaka	38.90
Kobe International University	151+	Private	Hyogo	24.10
Hokuriku University	151+	Private	Ishikawa	20.90
Kanagawa Dental University	151+	Private	Kanagawa	20.50
Akita International University	12	Public	Akita	20.40
Osaka University of Economics and Law	151+	Private	Osaka	20.10

Note: IntStud denotes the percentage of international students.

Of the seven universities in Table 1a, four universities do not appear in Table 1b. In fact, apart from Digital Hollywood University, which drops from 35.1% in Table 1a to 5.7% in Table 3b, Tokyo Fuji University, Okayama Shoka University, and Tokuyama University seem to have disappeared altogether in terms of IntStud after 2017. Of the seven universities in Table 1b, Osaka University of Tourism, Kanagawa Dental University, AIU, and Osaka University of Economics and Law are new entrants, although, as discussed previously, only AIU has a cardinal ranking, with the others being ranked above 151.

Table 2a,b show the universities with IntStud scores in the range of 10–20% for 2017 and 2018, respectively, with 14 of 16 and 14 of 21 being private universities in the two years. However, the two national universities, Tokyo Institute of Technology and Nagaoka University of Technology, are ranked at fourth and 17th, and fourth and 21st in Table 2a,b, respectively, while the remaining 14 universities are ranked outside the top 100. The seven national universities are ranked in the top 21 in Table 2b, with only Waseda University, Sophia University, and International Christian University, all of which are located in Tokyo, as the only private universities in the top 100. It is clear that the national universities dominate the rankings in the IntStud range 10–20%.

Table 2. (**a**) 10–20% IntStud 2017. (**b**) 10–20% IntStud 2018.

University	Rank	Type	Prefecture	IntStud
(**a**)				
Osaka University of Economics and Law	151+	Private	Osaka	16.70
Hagoromo University of International Studies	151+	Private	Osaka	15.50
Meikai University	141–150	Private	Chiba	14.90
Sanyo Gakuen University	151+	Private	Okayama	14.80
Nagoya Keizai University	151+	Private	Aichi	14.40
Takaoka University of Law	151+	Private	Toyama	12.70
Osaka Sangyo University	151+	Private	Osaka	12.50
Kanto Gakuen University	151+	Private	Gunma	11.70
Nagaoka University of Technology	17	National	Niigata	11.50
Ashikaga Institute of Technology	151+	Private	Tochigi	11.10
Seigakuin University	151+	Private	Saitama	11.00
Kibi International University	151+	Private	Okayama	10.70
Tokyo Institute of Technology	4	National	Tokyo	10.70
Tokyo International University	141–150	Private	Saitama	10.40
Nagasaki International University	151+	Private	Nagasaki	10.30
Reitaku University	101–110	Private	Chiba	10.30
(**b**)				
Nagoya Keizai University	151+	Private	Aichi	18.50
Josai International University	151+	Private	Chiba	17.40
Meikai University	151+	Private	Chiba	16.40
Tokyo International University	151+	Private	Saitama	16.00
Nagoya University of Commerce & Business	111–120	Private	Aichi	15.90
Hagoromo University of International Studies	151+	Private	Osaka	15.60
Shizuoka Eiwa Gakuin University	151+	Private	Shizuoka	15.60
Seigakuin University	151+	Private	Saitama	14.10
Osaka Sangyo University	151+	Private	Osaka	13.30
The University of Tokyo	1	National	Tokyo	12.40
Reitaku University	121–130	Private	Chiba	12.20
Tohoku University	3	National	Miyagi	11.60
Hitotsubashi University	14	National	Tokyo	11.50
Nagaoka University of Technology	21	National	Niigata	11.50
University of Tsukuba	9	National	Ibaraki	11.50
Tokyo Institute of Technology	4	National	Tokyo	10.90
Kyushu University	5	National	Fukuoka	10.60
Waseda University	11	Private	Tokyo	10.60
Nagasaki International University	151+	Private	Nagasaki	10.40
Sophia University	15	Private	Tokyo	10.40
International Christian University	16	Private	Tokyo	10.00

Note: IntStud denotes the percentage of international students.

Universities with IntStud scores in the range 5–10% for 2017 and 2018 are shown in Table 3a,b, respectively. Of the 35 universities in Table 3a, 18 are private, while 11 of 29 universities in Table 3b are private. These are much higher percentages than those in Tables 1 and 2. However, in Table 3a, 11 of the 17 non-private universities are ranked in the top 20, while only three private universities, namely Waseda University, International Christian University, and Sophia University, with rankings of 10th, 15th, and 18th, respectively, are listed in the top 100 universities.

Table 3. (**a**) 5–10% IntStud 2017. (**b**) 5–10% IntStud 2018.

University	Rank	Type	Prefecture	IntStud
(**a**)				
Hitotsubashi University	14	National	Tokyo	9.80
Nagoya University	4	National	Aichi	9.80
University of Tsukuba	9	National	Ibaraki	9.50
Sophia University	18	Private	Tokyo	9.40
Takushoku University	151+	Private	Tokyo	9.40
The University of Tokyo	1	National	Tokyo	9.20
Osaka University	6	National	Osaka	8.40
Tokyo University of Foreign Studies	27	National	Tokyo	8.00
Kyushu University	7	National	Fukuoka	7.90
Fukuoka Women's University	48	Public	Fukuoka	7.80
Tohoku University	2	National	Miyagi	7.50
Kyoto Gakuen University	151+	Private	Kyoto	7.40
Tokyo Medical and Dental University (TMDU)	38	National	Tokyo	7.20
Toyohashi University of Technology (TUT)	37	National	Aichi	7.20
Tokyo University and Graduate School of Social Welfare	151+	Private	Gunma	7.10
Waseda University	10	Private	Tokyo	7.10
Ashiya University	151+	Private	Hyogo	6.80
Hokkaido University	8	National	Hokkaido	6.70
Yamanashi Gakuin University	151+	Private	Yamanashi	6.70
Kyoto University	3	National	Kyoto	6.60
Utsunomiya Kyowa University	151+	Private	Tochigi	6.60
Tokyo University of Marine Science and Technology	36	National	Tokyo	6.50
Yokohama National University	33	National	Kanagawa	6.50
Toyama University of International Studies	151+	Private	Toyama	6.40
Baiko Gakuin University	151+	Private	Yamaguchi	6.10
Gifu Keizai University	151+	Private	Gifu	6.10
Hiroshima University	12	National	Hiroshima	5.80
International Christian University	15	Private	Tokyo	5.70
Musashino University	151+	Private	Tokyo	5.60
Musashino Art University	151+	Private	Tokyo	5.50
Ryutsu Keizai University	141–150	Private	Ibaraki	5.50
Kobe University	13	National	Hyogo	5.40
Tokyo Polytechnic University	151+	Private	Kanagawa	5.30
Sapporo University Women's Junior College	151+	Private	Hokkaido	5.20
Kyushu Sangyo University	121–130	Private	Fukuoka	5.10
(**b**)				
Fukuoka Women's University	62	Public	Fukuoka	9.00
Nagoya University	7	National	Aichi	8.70
Tokyo University of Foreign Studies	17	National	Tokyo	8.50
Tokyo Medical and Dental University (TMDU)	39	National	Tokyo	8.40
Yokohama College of Commerce	151+	Private	Kanagawa	8.20
Kyoto University	1	National	Kyoto	8.00
Yokohama National University	25	National	Kanagawa	7.80
Tokyo University of Marine Science and Technology	41	National	Tokyo	7.60
Hokkaido University	6	National	Hokkaido	7.50
Keio University	10	Private	Tokyo	7.30
Osaka University	8	National	Osaka	6.70
Hiroshima University	13	National	Hiroshima	6.60
Toyohashi University of Technology (TUT)	38	National	Aichi	6.60
Baiko Gakuin University	151+	Private	Yamaguchi	6.40
Musashino Art University	151+	Private	Tokyo	6.40
Tama Art University	151+	Private	Tokyo	6.30

Table 3. *Cont.*

University	Rank	Type	Prefecture	IntStud
Musashino University	151+	Private	Tokyo	6.20
Yamanashi Gakuin University	151+	Private	Yamanashi	6.10
The University of Electro-Communications	55	National	Tokyo	6.00
Kanazawa University	20	National	Ishikawa	5.90
Ritsumeikan University	23	Private	Kyoto	5.90
Kobe University	18	National	Hyogo	5.80
Digital Hollywood University	151+	Private	Tokyo	5.70
Kyoto University of Foreign Studies	92	Private	Kyoto	5.70
Tokyo University of the Arts	151+	National	Tokyo	5.60
Asia University	151+	Private	Tokyo	5.30
Saitama University	70	National	Saitama	5.20
Kyoto Institute of Technology	42	National	Kyoto	5.10
Ochanomizu University	32	National	Tokyo	5.10

Note: IntStud denotes the percentage of international students.

In Table 3b, eight of the 18 non-private universities are in the top 20, while 17 of 18 are in the top 100; the sole exception is Tokyo University of the Arts, having a ranking in the 151+ group. On the contrary, only three private universities of 11, namely Keio University, Ritsumeikan University, and Kyoto University of Foreign Studies, with rankings of 10th, 23rd, and 92nd, respectively, are listed in the top 100 in Table 3. As in Tables 1 and 2, national universities tend to dominate the rankings in terms of IntStud scores.

The plots between Rank and IntStud, and between Rank and FTE (Size), are shown in Figure 1a,b and Figure 2a,b, for 2017 and 2018, respectively. It is clear that there are positive linear relationships for Rank with IntStud and FTE (Size) in both years, especially if a single outlier was deleted in 2017 in Figure 1a, and two outliers were deleted in Figure 1b.

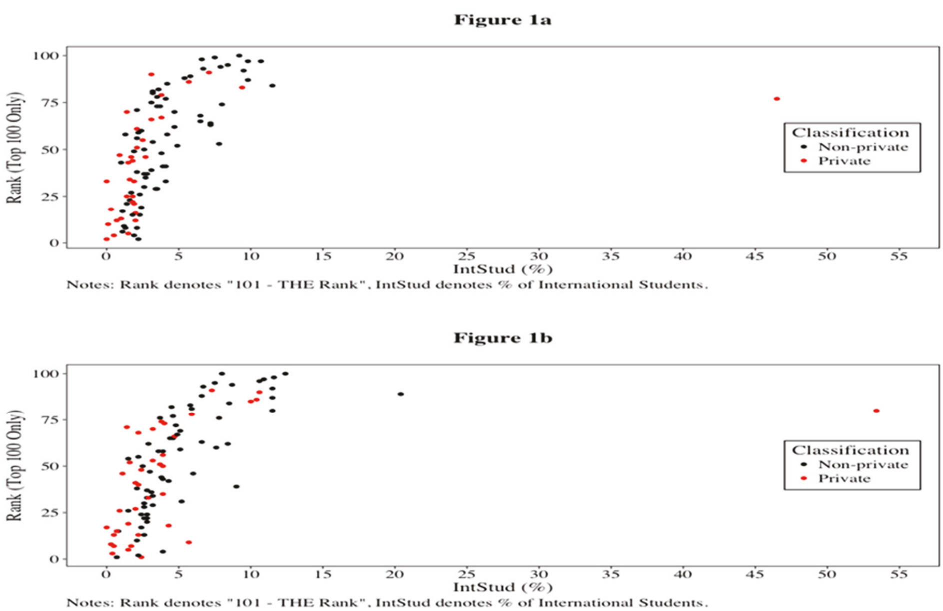

Figure 1. (**a**) Rank and Intstud, 2017; (**b**) Rank and Intstud, 2018.

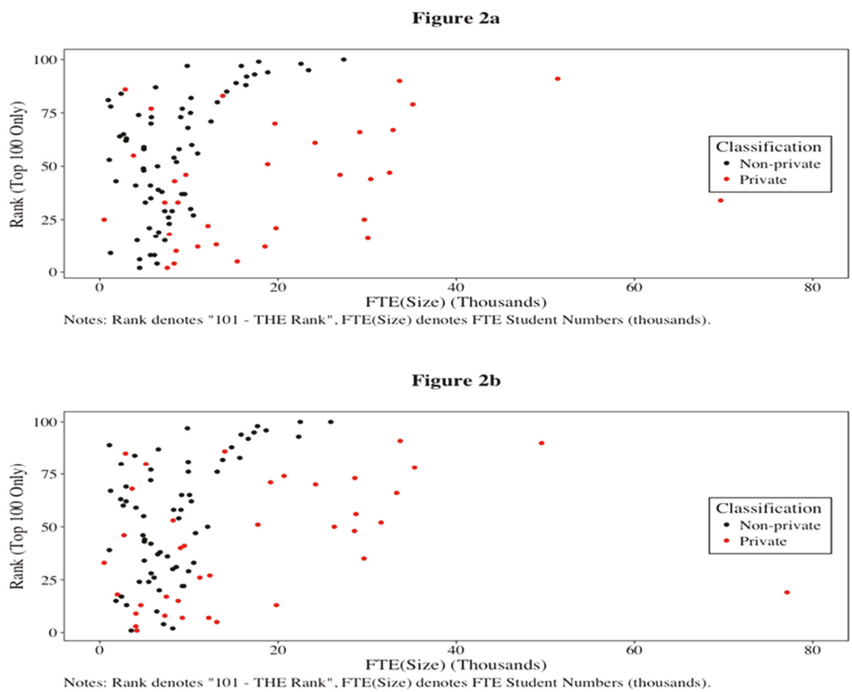

Figure 2. (**a**) Rank and FTE (Size), 2017; (**b**) Rank and FTE (Size), 2018.

The pairwise linear relationship between Rank and IntStud was steeper for private than for non-private universities in both 2017 and 2018, but there seems to be little difference from one year to the next. Unlike Figure 1a,b, the pairwise linear relationship between Rank and FTE (Size) was steeper for non-private than for private universities in Figure 2a,b in 2017 and 2018, respectively, with little apparent difference in the relationship between the two variables from one year to the next.

3. Empirical Analysis

As mentioned in Section 2, there are only 100 universities that are given cardinal rankings for 2017 and 2018. For this reason, only the first 100 leading universities in Japan were used for estimating and testing the effects of size and internationalization on the rankings of non-private (that is, national and public) and private universities.

The linear regression models to be estimated were variations of the following:

$$\text{Rank} = \text{intercept} + \text{a* IntStud} + \text{b* FTE (size)} + \text{error},$$

where Rank denotes "101—THE rank", IntStud denotes "% of international students", FTE (size) denotes "FTE student numbers (Thousands)", and the random error is presumed to satisfy the classical assumptions, which can be tested using the Breausch–Pagan test of homoskedasticity, the RESET test of no functional form misspecification, and the Jarque–Bera test of normality.

The estimates of the linear regression models, with the rankings being explained by IntStud and FTE (size), are based on 100 and 101 universities in 2017 and 2018, respectively, with 33 and 38 private universities, respectively, and 67 and 63 non-private universities, respectively, in 2017 and 2018. As the numbers of observations across the three tables, as well as for the two years, are different, the *R*-squared values cannot be compared.

The estimates of the linear regression models of Rank on IntStud and FTE (size) for all (that is, private and non-private) universities, private universities, and non-private universities in the top 100 universities, are given in Table 4a,c, respectively. The results for both years are presented in each table. "Rank" is defined as "101—THE rank", such that universities with a higher ranking are given a lower cardinal number.

Table 4. (**a**) Regressions of Rank on IntStud and number of full-time-equivalent students (FTE (size)) for the top 100 universities. (**b**) Regressions of Rank on IntStud and FTE (size) for private universities (from top 100). (**c**) Regressions of Rank on IntStud and FTE (size) for non-private universities (from top 100).

	2017	**2018**
	(**a**)	
Intercept	32.62 ***	30.08 ***
	(4.78)	(5.07)
IntStud	2.732 ***	2.479 ***
	(0.493)	(0.319)
FTE (size)	0.584 **	0.650 *
	(0.250)	(0.357)
Breusch–Pagan	48.23 ***	42.55 ***
Jarque–Bera	3.92	7.27 **
RESET	43.72 ***	45.44 ***
Wald Test	16.82 ***	33.49 ***
Observations	100	101
Adjusted R^2	0.254	0.301
Residual Standard Error	24.98 (df = 97)	24.43 (df = 98)
	(**b**)	
Intercept	24.43 ***	25.35 ***
	(6.70)	(7.86)
IntStud	1.509 ***	1.454 ***
	(0.138)	(0.214)
FTE (size)	0.623 *	0.623
	(0.309)	(0.383)
Breusch–Pagan	0.83	5.00 *
Jarque–Bera	1.80	1.13
RESET	14.02 ***	14.41 ***
Wald Test	60.62 ***	23.97 ***
Observations	33	38
Adjusted R^2	0.223	0.247
Residual Standard Error	24.42 (df = 30)	25.00 (df = 35)
	(**c**)	
Intercept	13.21 **	11.00 **
	(5.57)	(4.76)
IntStud	6.560 ***	5.067 ***
	(0.568)	(0.437)
FTE (size)	1.646 ***	1.985 ***
	(0.414)	(0.311)
Breusch–Pagan	9.05 **	1.09
Jarque–Bera	1.95	1.43
RESET	3.24 **	7.11 ***
Wald Test	68.49 ***	92.47 ***
Observations	67	63
Adjusted R^2	0.615	0.659
Residual Standard Error	17.84 (df = 64)	16.79 (df = 60)

Dependent Variable: Rank. **Notes:** Rank denotes "101—THE rank", IntStud denotes "% of international students", FTE (size) denotes "FTE student numbers (thousands)"; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

When the data for private and non-private universities from the top 100 universities were combined in Table 4a, both IntStud and FTE (size) were positive and statistically significant in both years. This is consistent with the pairwise findings in Figure 1a,b and Figure 2a,b that were discussed above. The estimated coefficients of IntStud and FTE (size) were separately similar for each of the two years.

The Lagrange multiplier tests for heteroscedasticity (Breusch–Pagan) were significant, but did not affect the validity of statistical inference as the standard errors were based on the Newey–West HAC consistent covariance matrix estimator. The Lagrange multiplier tests for non-normality (Jarque–Bera) were significant, which means that the errors were not normally distributed. Ramsey's RESET test for functional form suggests there may be some model misspecification, especially regarding the non-linearity of the relationship among Rank, IntStud, and FTE (size).

The regression estimates for private universities selected from the top 100 universities are given for the two years in Table 4b. Overall, the results are quantitatively similar to those in Table 4a, with the estimates being positive and statistically significant. In particular, the estimated coefficients of IntStud and FTE (size) were separately similar, not only for each of the two years, but also with the estimates for all universities in Table 4a, especially the estimated effects of FTE (size).

The Lagrange multiplier test for heteroscedasticity (Breusch–Pagan) was significant, but did not affect the validity of statistical inferences as the standard errors were based on the Newey–West HAC consistent covariance matrix estimator. The Lagrange multiplier test for non-normality (Jarque–Bera) was significant, which means that the errors were not normally distributed, Ramsey's RESET test for functional form suggests there may be some model misspecification, especially regarding the non-linearity of the relationship among Rank, IntStud, and FTE (size). The Lagrange multiplier tests for heteroscedasticity were either insignificant or marginally significant, while the Lagrange multiplier tests for non-normality were insignificant. The RESET functional form tests suggest there may be a non-linear relationship among Rank, IntStud, and FTE (size).

Table 4c presents the regression estimates for non-private universities selected from the top 100 universities for the two years. As compared with the estimates shown in Table 4a,b, the results are quantitatively dissimilar. Although the estimated coefficients of IntStud and FTE (size) were separately similar for each of the two years, with the estimates being positive and statistically significant in all cases, the estimates of the coefficients for both IntStud and FTE (size) were considerably larger than their counterparts in Table 4a,c for both 2017 and 2018.

The Lagrange multiplier test for heteroscedasticity (Breusch–Pagan) was significant for 2017 but not for 2018, while the Lagrange multiplier tests for non-normality (Jarque–Bera) were insignificant, which means that the errors were normally distributed for each of the two years. As in the case of Table 4a,b, Ramsey's RESET test for functional form suggests there may be some model misspecification, especially regarding the non-linearity of the relationship among Rank, IntStud, and FTE (size).

Overall, there seemed to be strong positive and statistically significant effects of both IntStud and FTE (size) on Rank in 2017 and 2018, regardless of whether the data for the top 100 private and non-private universities were combined, as in Table 4a, or examined separately, as in Table 4b,c.

4. Concluding Remarks

As international and domestic rankings are typically based on arbitrary methodologies and criteria, evaluating how the rankings might be sensitive to different factors, as well as forecasting how they might change over time, requires a statistical analysis of the factors that affect the rankings. The Times Higher Education (THE) World University Rankings represent a leading and influential annual source of international university rankings.

Using recently released data for Japan, the paper evaluated the effects of size (specifically, the number of full-time-equivalent (FTE) students, or FTE (size)) and internationalization (specifically, the percentage of international students, or IntStud) on academic rankings using THE data for 2017 and 2018 on national, public (that is, prefectural or city), and private universities. The results showed that both FTE (size) and IntStud were statistically significant in explaining rankings for all universities, as well as separately for private and non-private (that is, national and public) universities, in Japan for 2017 and 2018.

As discussed in Section 1, the purpose of the paper was to answer the following questions (the answers are given in **bold**):

(i). Are private or non-private universities more highly ranked? (**Non-private**)
(ii). Are private or non-private universities larger in terms of size? (**Private**)
(iii). Do private or non-private universities have a higher degree of internationalization? (**In general, private**)
(iv). Do the size, internationalization, and rankings of private and non-private universities change over time? (**Slightly**)
(v). Are there differences in the effects of size and internationalization on the rankings of private universities? (**Yes**)
(vi). Are there differences in the effects of size and internationalization on the rankings of non-private universities? (**Yes**)
(vii). Do the effects of size and internationalization change over time for private and non-private universities? (**Not between 2017 and 2018**)

Further empirical analysis could be undertaken for private and non-private universities in Japan, as well as for the US, Europe, Asia, and Latin America; however, the distinction between private and non-private universities is prevalent primarily for the US.

A deeper analysis of the issue requires much richer data, which might be forthcoming in the foreseeable future. Limitations of the analysis include the late arrival of some data series, which can make the prediction of rankings problematic.

The paper is intended for the Special Issue of the journal on "Sustainability of the Theories Developed by Mathematical Finance and Mathematical Economics with Applications". In this sense, the paper is an application of applied econometrics to evaluate and predict university rankings using size and internationalization from the Times Higher Education (THE) data for Japan.

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Relationship among HIV/AIDS Prevalence, Human Capital, Good Governance, and Sustainable Development: Empirical Evidence from Sub-Saharan Africa

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Abstract: Sub-Saharan Africa is regarded as the region that accommodates about 75% of the world HIV/AIDS prevalence as of 2016. Research on the relationship between the epidemic and sustainable development is scant in this part of the world, as available literature is dominated by studies that focus on HIV and economic growth. Therefore, this study examines the relationship between sustainable development and HIV/AIDS prevalence, along with other determinants of sustainable development, such as good governance and human capital in 26 sub-Saharan Africa countries over a 27-year period from 1990—2016. The pooled mean group (PMG) estimator was employed for analysis after it was confirmed by the Hausman test for the estimation of the relationship among the variables. The results revealed a unidirectional long-run and significant relationship between HIV/AIDS prevalence and sustainable development, human capital and good governance, and human capital and sustainable development. Also, a bidirectional long-run relationship was found between good governance and HIV/AIDS prevalence. Estimation of subgroups provides a robustness check for our findings. Therefore, the paper gives new insight to the government of sub-Saharan Africa countries and major stakeholders about how to attain sustainable development in the region, while intensifying efforts on reducing HIV/AIDS prevalence, and at the same time ensuring effective good governance and human capital development.

Keywords: sustainable development; HIV/AIDS; human capital; good governance; sub-Saharan Africa

1. Introduction

Globally, the prevalence of HIV/AIDS constitutes a hindrance to the advancement of human development and remains a major concern for researchers, stakeholders, and policymakers [1]. With reference to the report of Joint United Nations Programme on HIV/AIDS [2], it was estimated at the end of 2016 that 34.5 million adults globally have been infected with HIV/AIDS virus, while about one million died from AIDS-related diseases. In the same year, about 25.73 million (almost 75% of the world HIV/AIDS prevalence) people were HIV/AIDS carrier in Africa, out of which 741,000 died as a result of AIDS-related illnesses. [2].

Today, the HIV/AIDS epidemics remains one of the challenges facing Africa continent, as it is far more than a health issue, and still requires more efforts so as not to hinder the sustainable development of the region [3,4]. However, in order to avert the reverse of the development, the issue of sustainable development has taken a center stage position, both in the academia and among various stakeholders and policymakers.

It was noted that the world is facing great challenges in terms of development sustainability. On one part, there is a high number of people that are living below standard, even when there is overdependence on natural resources, most especially in the developing countries. On the other part, there are an important economic (poverty, inequality, etc.), social (health), and environmental (climate change) crises, which sometimes culminate into an epidemic and result in death [5,6].

Though studies abound on the definition of sustainable development, a definition by World Bank simply put it as development path or structured principles that could be maintained to ensure that total welfare of the people does not decline along the development path [7]. An important point of reference for sustainable development is the report published in 1987 by Brundtland Commission entitled *Our Common Future* [8]. According to this report, sustainable development is conceptualized as the actions or principles put in place that will enable the people to meet their present needs without compromising the ability of future generations to meet their own needs [8].

Achieving sustainable development involves economic, social, and quality environment. These three pillars must be evenly and wholly integrated within the process of improving development. In respect of social dimension, *Our Common Future* reports argue that sustainable development requires meeting the requisite needs of the citizens and extending to them the opportunity to accomplish their aspirations for a better life [9]. It is worthy to note that the report did not limit the pillars of sustainable development to the economic, social, and environment, but also includes other aspects that were not broadly considered, for instance, good governance. It is believed that such equity in achieving sustainable development will be enhanced by an effective political system and rule of law that secure effective citizen participation in decision-making.

The sustainable development agenda for 2030 has a health issue at the center [10]. One of the goals of this agenda is "to ensure healthy lives and promote well-being for all citizens at all ages." In order to meet this target, there is a need to examine the various factors that could hinder the achievement of the goals. Among the ones highlighted which could do this is the infectious disease (e.g. HIV/AIDS) [10]. Health is as inherently significant as human rights and is also important to achieving the pillars of sustainable development (economic development, environmental sustainability, social inclusion, and good governance). Sustainable development will be elusive in the absence of health and productive population. There is a report which details that combating the spread of HIV/AIDS is critical to human progress, as this disease disproportionately affect the development potential of dozens of countries [11]. HIV/AIDS has a complex linkage with poverty and, in turn, to the larger sustainable development [12].

There is no doubt that the consequences of the epidemic in sub-Saharan Africa would have a great impact on sustainable development in the region if the scenario continues.

2. Literature Review

The studies on HIV/AIDS and economic growth have been prolific. Among them is the one on HIV and economic growth in 30 sub-Saharan Africa countries, which revealed that AIDS has a significant negative impact on GDP [13]. Reference [13] found that the negative impact of the epidemic will reduce the growth rate of per capital income in the average number of countries studied and concluded that the larger impact will be felt on the 10 countries with the highest HIV prevalence in those 30 sub-Saharan Africa countries. A similar study was conducted in South Africa, which is among the countries with the highest HIV prevalence in sub-Saharan Africa. The study corroborated over Reference [13] and concluded that in the presence of HIV prevalence, South Africa economic growth will decline in GDP by about 17% [14]. This finding was corroborated by subsequent studies [15,16]. In 2000, a similar study was conducted which forecasted that the situation of HIV in Lesotho will cause the GDP of the country to decline by 2010 [17]. Meanwhile, Maijama and Samusidin [16] found in their study that the current HIV prevalence in sub-Saharan Africa has a negative effect on GDP per capital growth. A similar study was previously conducted by Augier and Yaly [18], which modeled diseases with the highest mortality rates, among which is AIDS as it affects economic growth. The result showed that poor health due to these infectious diseases has effects on decreasing economic growth of any country where the epidemic is prevalent. However, a contrary view was held by another author on HIV/AIDS. His study found no statistically significant impact of HIV/AIDS on GDP [19]. Meanwhile, Afawubo and Mathey [20] conducted a study on the factors influencing HIV/AIDS prevalence. The study found that human capital has a short-run causal impact on HIV prevalence but found a negative relationship between HIV and economic growth and concluded that GDP growth is not a driver for HIV prevalence across the West African countries [20]. Alemu et al. investigated the effect of HIV on the manufacturing sector in Lesotho and South Africa. The study concluded that there is a negative significant impact of the HIV on the productivity growth of the two countries [21]. This study was in agreement with Young, who revealed a significant impact of HIV/AIDS on human capital which, in turn, affects economic growth in sub-Saharan Africa [22]. The subsequent study established a long-term impact of HIV/AIDS on economic growth [23]. However, contrary results were found when studies were conducted on how much of a threat a mature AIDS epidemic is to economic growth. The study revealed that AIDS is not likely to threaten economic growth, either through human capital or accumulation channels. [17,19,24]. The relationship between HIV/AIDS prevalence and human capital in sub-Saharan Africa was found to be negative and statistically significant [25]. These findings were not different from the findings of other authors, who concluded in their studies that poor health as a result of an infectious disease has an impact on the economic growth of any country where it is prevalent [18,26].

In a more recent study, several authors empirically established the impact of HIV/AIDS prevalence on economic growth [15,16,27,28]. Their studies found a long-run relationship between HIV/AIDS prevalence and economic growth and argued that, in the long-run, HIV/AIDS will have a devastating impact on economic growth. In another dimension, the impact of HIV/AIDS on human capital was empirically examined and the results showed that HIV/AIDS prevalence have a long-run impact on human capital [16,20]. The argument from the studies was that as the HIV/AIDS prevalence increases, the country human capital decreases. Meanwhile, Shuaibu and Oladapo [29] were able to establish a long-run relationship between human capital economic growth and good governance in their study on Africa countries using a panel model. The study argued that economic growth and good governance are drivers for human capital development. In all the reviewed literature, none of the studies attempted to model the HIV and sustainable development.

Meanwhile, there are multiple dimension of views on sustainable economic development and good governance. Of importance to this study is the view of Brautigam on governance and economy which put it as a neutral concept, meaning "the political direction and control exercised over the actions of the members, citizens or inhabitants of communities, societies and states" [30] (p.3). The author argued in his book that the impact of good governance on a country economic growth cannot be neglected. In his view, political accountability, an effective rule of law, and transparency are some of the significant ingredients of good governance that impact on economic development. Good governance is considered to be the recent concept that recognized the functions of the state in the economy, where the involvement of all stakeholders is significant in the process of achieving sustainable economic development [7]. Stojanovic et al. noted that the central place of development policy is occupied with the model of good governance, which has become the cornerstone of sustainable development [31].

The relationship between good governance and development sustainability received great attention in scholarly enquiry [7,31]. The literature on the relationship is mixed, as there are both opposing and supporting views on the issue. An observation was made that, while few studies addressed the influence of good governance on sustainable development, some authors found that good governance is not a determinant factor for sustainable development [7]. Those studies found that relationship opined that good governance to demand voice and accountability to the citizen and rule of law guiding economic transactions, regulatory quality, control of corruption, the ability of the government to be effective, and an environment devoid of war/terrorism.

Various studies established a relationship between sustainable economic development and good governance [7,32,33], while some show no relationship between the two variables [34,35]. Though Stojanovic et al. revealed a statistical significance, direction, and significance of the effect of good governance, the study, however, suggested that there is no "one size fits all" model of good governance [31]. In view of the mixed results on the relationship between good governance and sustainable development, it is pertinent to follow the findings of Stojanovic et al. and examine the relationship between good governance and sustainable development in different regions.

The impact of human capital on sustainable development cannot be downplayed. Various literature abound on the human capital and sustainable development. The linkage among population, economic growth, employment, education, and sustainable development was examined and the study revealed that human capital is significant to sustainable development and efforts to ensure the synergy depends on the effective approach adopted [36]. This was corroborated by another author who opined that human capital faster rate of development of the society contributes to the sustainability of the society and ensures equitable distribution of development benefits [37]. Scicchitano [38] demonstrated in his study that human capital composition (research and development), which was in the past not considered in the endogenous growth model, was found to be significant in determining economic growth rate. Also, it was found in the recent studies that human capital increase led to sustainable economic growth [39,40]. Similarly, in EU states, a study was conducted and found that human capital is directly influencing sustainable development [41]. In a reversed case, Shuaibu and Oladapo [29] found economic growth as one of the drivers for human capital development.

It is evident from the literature reviewed that studies on sustainable economic development and human capital has not been well researched in sub-Saharan Africa countries. The available ones are country-specific and are primarily focused on the traditional parameters of measuring country economic development (i.e., GDP); human development index (HDI), and educational attainment for human capital [42]. The study of Shuaibu and Oladayo was tilted study toward determining factors contributing to human capital development using 33 African countries. The study confirmed a significant long-run relationship between health and human capital development and also institutions (good governance) [29]. However, it argues that short-term gains may be achieved through enhanced institutional quality.

The idea that HIV/AIDS may have a significant impact on sustainable development is understandable, for the simple reason that "health is wealth." As a consequence, one would expect HIV/AIDS to have an influence on sustainable development. It is therefore surprising that although there is an extensive empirical literature on sustainable development, HIV/AIDS prevalence, and economic growth in developing countries, most especially African countries where the epidemic is ravaging, research on how the HIV/AIDS could impact on sustainable development are scant.

To date, however, and to the best of our knowledge, the relationship between HIV/AIDS and sustainable economic growth in sub-Saharan Africa countries has not been thoroughly dealt with in empirical literature, and this study will contribute to the literature on this important topic.

The main thrust of this paper is to analyze the relationships among HIV/AIDS, good governance, human capital, and sustainable development in sub-Saharan Africa. This study will investigate through the long and short-run dynamic relationship following the sustainable development framework proposed by World Bank. Consequently, it will contribute empirically to the literature on the relationship between HIV/AIDS and sustainable development in sub-Saharan Africa by employing a more recent panel data estimator by Pesaran et al.

3. Data and Methods

3.1. Data

In order to achieve the objective of the study, variables such as HIV/AIDS prevalence rate, country-level governance index, and human capital index were selected to examine their relationship with sustainable economic development. The adjusted net savings was measured as the gross national savings, less the value of consumption of fixed capital. This variable was established to be a good indicator for sustainable development [43–46]. Prevalence of HIV/AIDS, measured as the percentage of people aged between 15—49 who are infected with HIV, was utilized in previous studies [1,3,13–15,19]. The country-level governance index was measured with six indices: Voice and accountability, rule of law, regulatory quality, control of corruption, government effectiveness and political stability, and absence of violence/terrorism (see Table 1). In order to compute the indices into a single variable, the average rank of each country in the panel for the six indices was computed for individual years. This index was used by previous researchers [7,31]. For measuring human capital, we employed human capital index [47]. This was employed based on the arguments in the literature on the non-consensus on the human capital index, which prompted the Penn World Table to introduce another index in PWT version 8 that was computed using the data from Barro and Lee and an assumed rate of return to education based on Mincer equation estimates [47,48].

These variables are sourced from the World Development Bank Indicator [49], Word Governance Indicator [50], and Penn World Table [47]. The data are yearly and cover the period 1990—2016. The countries included in the panel are 26 sub-Saharan African countries (see Appendix Table A1). The choice of countries in the panel was based on the availability of data for the variables included in the study during the observed period.

Table 1. Description of variables.

Code Name	Variable	Proxy	Definition	Measurement Unit	Source
HPREV	HIV/AIDS	HIV/AIDS prevalence	Prevalence of HIV refers to the percentage of people ages 15—49 who are infected with HIV	Percentage	World Bank Development Indicators
HCI	Human Capital	Human capital index	Human capital is measured as the discounted value of earnings over a person's lifetime	Based on average years of schooling and returns to education	World Penn Table
CLG	Good governance	Country level governance	It is the perception on the efficiency of government in the following areas: Voice and Accountability, Rule of Law, Regulatory Quality, Control of Corruption, Government Effectiveness, and Political stability and absence of Violence/Terrorism.	Percentile Rank	World Governance Indicator
ANS	Sustainable development	Adjusted net saving	Adjusted net savings are equal to net national savings plus education expenditure and minus energy depletion, net forest depletion, and carbon dioxide	Percentage	World Bank Development Indicator

3.2. Method

Following the sustainable development framework developed by the World Bank, this paper follows the one released by the World Bank and it's based on the crude estimate as follows:

ANS = NNS + E – R – P

where ANS is the adjusted net saving, NNS is the Net National Saving, E is the Current education expenditure, R is the Resource rents, and P is the Carbon dioxide (CO2) damage.

In the calculation of sustainable development (ANS) in this study, current expenditure is treated as saving rather than consumption, since it increases the country's human capital (human capital is being considered here as a proxy), and pollution damages seek to reflect losses of welfare in the form of human sickness (HIV/AIDS prevalence as a proxy). Energy depletion is the depletion of oil, coal, and natural gas. A measure of depletion stands for the management of the natural resources (country-level governance index as a proxy).

For the empirical analysis, the study is based on Pesaran et al. methodology, which introduced the pooled mean group (PMG) approach in the panel ARDL framework [51]. This estimator was settled as a result of its advantages in comparison with other panel estimators. First, PMG/panel ARDL does not require a formal test for cointegration. Second, PMG minimizes the endogeneity problems and all the variables are considered to be endogenous. Third, the testing for the order of variables integration is not generally required, i.e either the variable is I(0) or I(1) is not an issue in PMG. Last, the long-run and short-run variables are estimated simultaneously, lessening problems of omitted variables and autocorrelation.

Therefore, based on Pesaran et al. methodology, the panel ARDL model for this study including the long-run relationship between the variables is presented as follows:

$$\begin{aligned}\Delta ANS_{it} = {} & \alpha_i + \textstyle\sum_{j=1}^{p-1} \beta_{ij} \Delta ANS_{i,t\text{-}j} + \sum_{r=0}^{n-1} \gamma_{ir} \Delta HCI_{i,t\text{-}r} + \sum_{i=0}^{q-1} \varphi_{il} \Delta HPREV_{i,t\text{-}l} + \\ & \textstyle\sum_{c=0}^{m-1} \tau_{ic} \Delta CLG_{i,t\text{-}c} + \delta_1 ANS_{i,t\text{-}1} + \delta_2 HCI_{i,t\text{-}1} + \delta_3 HPREV_{i,t\text{-}1} + \delta_4 CLG_{i,t\text{-}1} + \varepsilon_{1i,t}\end{aligned} \tag{1}$$

$$\begin{aligned}\Delta HCI_{it} = {} & \alpha_i + \textstyle\sum_{j=1}^{p-1} \beta_{ij} \Delta HCI_{i,t\text{-}j} + \sum_{i=0}^{q-1} \varphi_{il} \Delta ANS_{i,t\text{-}l} + \sum_{r=0}^{n-1} \gamma_{ir} \Delta HPREV_{i,t\text{-}r} \\ & + \textstyle\sum_{c=0}^{m-1} \tau_{ic} \Delta CLG_{i,t\text{-}c} + \omega_1 HCI_{i,t\text{-}1} + \omega_2 ANS_{i,t\text{-}1} + \omega_3 HPREV_{i,t\text{-}1} + \omega_4 HPREV_{i,t\text{-}1} + \varepsilon_{2i,t}\end{aligned} \tag{2}$$

$$\begin{aligned}\Delta HPREV_{it} = {} & \alpha_i + \textstyle\sum_{j=1}^{p-1} \beta_{ij} \Delta HPREV_{i,t\text{-}j} + \sum_{i=0}^{q-1} \varphi_{il} \Delta HCI_{i,t\text{-}l} + \sum_{r=0}^{n-1} \gamma_{ir} \Delta ANS_{i,t\text{-}r} + \\ & \textstyle\sum_{c=0}^{m-1} \tau_{ic} \Delta CLG_{i,t\text{-}c} + \pi_1 HPREV_{,t\text{-}1} + \pi_2 HCI_{i,t\text{-}1} + \pi_3 ANS_{i,t\text{-}1} + \pi_4 CLG + \varepsilon_{3i,t}\end{aligned} \tag{3}$$

$$\begin{aligned}\Delta CLG_{it} = {} & \alpha_i + \textstyle\sum_{j=1}^{p-1} \beta_{ij} \Delta CLG_{i,t\text{-}j} + \sum_{i=0}^{q-1} \varphi_{il} \Delta HCI_{i,t\text{-}l} + \sum_{r=0}^{n-1} \gamma_{ir} \Delta ANS_{i,t\text{-}r} \\ & + \textstyle\sum_{c=0}^{m-1} \tau_{ic} \Delta HPREV_{i,t\text{-}c} + \Omega_1 CLG_{,t\text{-}l} + \Omega_2 HCI_{i,t\text{-}l} + \Omega_3 ANS_{i,t\text{-}l} + \Omega_4 HPREV + \varepsilon_{4i,t}\end{aligned} \tag{4}$$

where *ANS, HPREV, HCI,* and *CLG* are adjusted net saving (a proxy for sustainable development), HIV/AIDS prevalence rate, human capital index, and country-level governance. Δ and $\sum k_{it}$ $(k = 1, 2, 3, 4)$ are the first difference operator and a white noise term. Also, in Equations (1—4), α_1 denotes a country-specific intercept. The subscript *I* denotes a specific unit and varies from *1* to *N*. A reasonable generalization of cointegration test from time series to panel data may formulate the H_0 of no cointegration between the four variables in Equation (1) as follows: H_0: $\delta_1 = \delta_2 = \delta_3 = \delta_4 = 0$, while H_1: At least one $\delta k \neq 0$ $(k = 1,2,3,4)$.

Similarly, the null hypothesis of no cointegration in Equation (2) may be written as H_0: $\omega_1 = \omega_2 = \omega_3 = \omega_4 = 0$. Also, in Equation (3,4), the H_0 of no cointegration between the four variables may be formulated as H_0: $\pi_1 = \pi_2 = \pi_3 = \pi_4 = 0$, *and* $\Omega_1 = \Omega_2 = \Omega_3 = \Omega_4 = 0$

Subsequently, if the null hypothesis of cointegration is rejected, we estimate the long-run relationship for the first panel ARDL described in Equation (1) is presented as follows:

$$ANS_{it} = \mu_i + \sum_{j=1}^{p-1} \lambda_{1j} ANS_{i,t\text{-}j} + \sum_{i=0}^{q-1} \lambda_{2j} HCI_{i,t\text{-}l} + \sum_{r=0}^{n-1} \lambda_{3j} HPREV_{i,t\text{-}r} + \sum_{c=0}^{m-1} \lambda_{4j} CLG_{i,t\text{-}c} + v_{1i,t} \tag{5}$$

Consequent to the above model specification, the assumption of PMG estimator of the coefficient of the long-run relationship to be the same for every country in the panel were considered. Meanwhile, the assumption is also considered in the null hypothesis of no cointegration model specification for the four models. Similarly, the remaining three models were specified in line with Equation (5).

The error correction models for the ARDL models described above are constructed as follows:

$$\Delta ANS_{it} = \alpha_i + \sum_{j=1}^{p-1} \beta_{ij} \Delta ANS_{i,t\text{-}j} + \sum_{i=0}^{q-1} \varphi_{il} \Delta HCI_{i,t\text{-}l} + \sum_{r=0}^{n-1} \gamma_{ir} \Delta HPREV_{i,t\text{-}r} + \sum_{c=0}^{m-1} \tau_{ic} \Delta CLG_{i,t\text{-}c} + aECT_{t\text{-}1} + e_{1i,t} \tag{6}$$

$$\Delta HCI_{it} = \alpha_i + \sum_{j=1}^{p-1} \beta_{ij} \Delta HCI_{i,t\text{-}j} + \sum_{i=0}^{q-1} \varphi_{il} \Delta ANS_{i,t\text{-}l} + \sum_{r=0}^{n-1} \gamma_{ir} \Delta HPREV_{i,t\text{-}r} + \sum_{c=0}^{m-1} \tau_{ic} \Delta CLG_{i,t\text{-}c} + bECT_{t\text{-}1} + e_{2i,t} \tag{7}$$

$$\Delta HPREV_{it} = \alpha_i + \sum_{j=1}^{p-1} \beta_{ij} \Delta HPREV_{i,t\text{-}j} + \sum_{i=0}^{q-1} \varphi_{il} \Delta ANS_{i,t\text{-}l} + \sum_{r=0}^{n-1} \gamma_{ir} \Delta HCI_{i,t\text{-}r} + \sum_{c=0}^{m-1} \tau_{ic} \Delta CLG_{i,t\text{-}c} + cECT_{t\text{-}1} + e_{3i,t} \tag{8}$$

$$\Delta CLG_{it} = \alpha_i + \sum_{j=1}^{p-1} \beta_{ij} \Delta CLG_{i,t\text{-}j} + \sum_{i=0}^{q-1} \varphi_{il} \Delta HCI_{i,t\text{-}l} + \sum_{r=0}^{n-1} \gamma_{ir} \Delta ANS_{i,t\text{-}r} + \sum_{c=0}^{m-1} \tau_{ic} \Delta HPREV_{i,t\text{-}c} + dECT_{t\text{-}1} + e_{4i,t} \tag{9}$$

where the error term $e_{ki,t}$ $(k = 1,2,3,4)$ is independently and normally distributed with zero mean and constant variance, and $ECT_{t\text{-}1}$ is the error correction term specified from the long-run equilibrium relationship. The coefficient of a, b, c, d shows the speed of adjustment to the equilibrium level in the presence of shock.

In addition to the specified model above, Pesaran et al. proposed two other estimators that could be applied when both time and cross sections are large. Pooled mean group (PMG) and mean group (MG) difference are that MG estimator is more effective when there is variation in the slope and intercept among the countries in the panel, whereas PMG assumed homogeneity of slope and intercepts among the countries. Also, dynamic fixed effect (DFE) was proposed to be considered where the slope is constant, but the intercept could vary across the countries.

In order to enhance the robustness of our findings, the panel was subdivided into subgroups. This classification into subgroup (upper middle income –UMIC, low middle income – LMIC, and low income – LIC) was based on the 2018 World Bank country's classification according to level of economies.

Meanwhile, it is often assumed that errors in panel data are cross-sectional independent in most cases when the cross-section dimension (N) is large [52]. Evidence abounds in the literature that proved the presence of cross-sectional dependence (CD) in panel model. Pesaran et al. [52] argued that failing to give adequate consideration to cross-sectional dependence in estimation could give loss of estimator efficiency and insignificant test statistics. In view of these, Pesaran's CD test was employed to test for cross-sectional dependency in our data. Moreover, Westerlund [53] observed that many studies failed to reject the no-cointegration hypothesis, which was centered on the fact that most residuals-based cointegration tests require that the long-run parameters for the variables in their levels are equal to the short-run parameters for the variables. In view of the above, this study employed Westerlund's [53] error-correction-based cointegration tests that are based on structural, instead of residual, dynamic, which do not enforce any common-factor restriction to examine the existence of long-run relationship among our variables.

Having specified the models according to Pesaran et al., the next step is to give descriptive statistics on the data, which will enable us to show and explain the characteristics of each variable in the model. Subsequently, the unit root test was conducted to ascertain that no variable is integrated of order two. This is to ensure that the model does not violate the assumption of PMG [51]. Last, analysis was done and inferences from the analysis were made to draw a conclusion.

4. Empirical Findings

4.1. Descriptive Statistics

As revealed in Table 2, while the average adjusted net savings (ANS) in the group panel is -3.62, the UMIC group has the highest mean value for ANS, followed by LIC and LMIC groups. However, greater variation was observed in LMIC, which shows a standard deviation value of 32.81 compared to the group panel, UMIC, and LIC, which have 21.96, 13.75, and 11.49, respectively.

Table 2. Characteristics of the variables.

	Statistics	ANS	HIVPREV	HCI	CLG
Group Panel	Mean	−3.62	5.19	1.62	−0.56
	Max.	47.93	29.4	2.91	0.99
	Min.	−210.90	0.1	1.03	−2.1
	Std.Dev	21.96	6.61	0.40	0.56
	Obs.	697	702	702	624
UMIC	Mean	11.60	12.34	2.26	0.24
	Max.	37.58	27	2.81	0.88
	Min.	−26.99	0.6	1.77	−0.67
	Std.Dev.	13.75	8.03	0.27	0.43
	Obs.	105	108	108	96
LMIC	Mean	−9.21	5.25	1.67	−0.81
	Max.	47.83	28.4	2.38	0.12
	Min.	−210.90	0.2	1.14	−1.66
	Std.Dev.	32.81	7.18	0.29	0.42
	Obs.	231	216	216	192
LIC	Mean	−4.73	3.11	1.40	−0.64
	Max.	36.06	14.9	2.17	0.05
	Min.	−47.21	0.1	1.03	−2.1
	Std.Dev.	11.49	3.81	0.24	0.46
	Obs.	369	378	378	336

ANS = Adjusted net savings, HIVPREV = HIV/AIDS Prevalence, HCI = Human capital index, CLG = Country-level governance. UMIC = Upper-middle income countries, LMIC = Low-middle income countries, LIC = Low income countries.

The average mean value of HIV/AIDS prevalence for the group panel is 5.19, UMIC has a 12.34 mean value for HIV/AIDS, while LMIC and LIC have 5.25 and 3.11, respectively. Meanwhile, the standard deviation shows that there is high deviation from the mean value in UMIC with a standard deviation value of 8.03 compared to 6.61, 7.18, and 3.81, which are values for group panel, LMIC, and LIC, respectively.

The average human capital index in UMIC is higher than the other groups. This is expected being an upper-middle income country. However, all the groups show a minimal standard deviation value, which could be an indication that each group possess similar characteristic in terms of human capital. The country level governance could be described to be fair in UMIC by having a mean value of 0.24 compared to the average value for the group panel, which is -0.56, while -0.81 and -0.64 are for LMIC and LIC, respectively.

4.2. Cross-Dependency Test

In line with Pesaran et al. [54] cross-dependency test, the null hypothesis is that there is no cross-section dependence (correlation in residuals). The results from the test presented in Table 3, which shows that this study failed to reject the null hypothesis of no cross-sectional dependency in all the four panels. It implies that the panels are free from the cross-sectional dependency problem.

Table 3. Pesaran cross-sectional dependency test.

	Statistics	Prob.
Group Panel	1.01	0.31
UMIC	−0.63	0.53
LMIC	−1.58	0.12
LIC	1.06	0.29

UMIC = Upper-middle income countries, LMIC = Low-middle income countries, LIC = Low income countries.

4.3. Unit Root Test

Pesaran et al. commented that the variables for PMG estimator could either be integrated on *I(0)* or *I(1)* in order for the variable not to lose its predictive power [51]. However, Kumar et al. opined that panel ARDL does not generally require a knowledge of the order of integration of variables [55]. Nevertheless, we apply Im, Pesaran, and Shin (IPS) W-stat test for both levels and their first difference with an intercept and trend. This was done to ascertain the stationary properties of the variable to enhance the robustness of our results and ensure that none of the variables is integrated at order *(2)*. The results as presented in Table 4. The IPS statistics, as revealed in the table, indicate that for the group panel, three out of the four variables are integrated at order *(0)*, while country-level governance is integrated at order *(1)*. In the UMIC panel, HIVPREV and *CLG* integrated at order *(0)*, while *ANS* and *HCI* integrated at order *(1)*. However, the stationary property of the variables in the LMIC panel is a bit different, in the sense that *HCI* integrated at order *(0)* only with intercept. Last, in the LIC panel, both *ANS* and *HIVPREV* integrated at order *(0)*, while *HCI* and *CLG* integrated at order *(1)*. In summary, the variables across the four panel were tested both at intercept, an intercept and trend. The results, as presented in Table 4, indicate that none of the series are integrated at order *(2)*. Therefore, it is safe for us to employ PMG estimator.

Table 4. Im, Pesaran, and Shin (IPS) Panel unit root result.

		Level		1st Difference	
	Variable	**Intercept**	**Intercept and Trend**	**Intercept**	**Intercept and Trend**
Group Panel	ANS	−5.55*	−4.77*	-	-
	HIVPREV	−20.32*	−20.22*	-	-
	HCI	−2.05**	2.22	-	−5.17*
	CLG	−0.35	−1.37	−17.66*	−15.93*
UMIC	ANS	−0.79	−0.99	−8.42*	−15.93*
	HIVPREV	−16.12*	−10.29*	-	-
	HCI	0.30	0.91	−2.77*	−6.96*
	CLG	−0.39	−2.15*	−9.94*	-
LMIC	ANS	−4.28*	−5.10*	-	-
	HIVPREV	−8.21*	−6.14*	-	-
	HCI	−2.32*	1.87	-	−0.66
	CLG	−0.98	−2.65*	−9.91*	-
LIC	ANS	-3.92*	−2.03**	-	-
	HIVPREV	−13.31*	−17.92*	-	-
	HCI	−1.20	1.10	−5.89*	−4.71*
	CLG	0.49	1.43	−11.30*	−9.98*

*, ** indicates 1% and 5% significance level respectively. UMIC = Upper-middle income countries, LMIC = Low-middle income countries, LIC = Low income countries.

4.4. Cointegration Analysis

The Westerlund ECM panel cointegration tests consists of four tests designed to test cointegration in panel data. The first two tests were to test the alternative hypothesis that the panel is cointegrated as whole, while the other two tests were to test that at least one unit is cointegrated. However, the results from the test, as shown in Table 5, reveals that the three tests out of four in group panel strongly reject the null hypothesis of no cointegration among the variables. Two tests accepted alternative hypothesis that there is cointegration among the variables in UMIC panel, and three tests strongly rejected null hypothesis of no cointegration in LMIC panel. Meanwhile, the test results failed to reject the null hypothesis of no cointegration in LIC panel. In summary, there is strong evidence that there is cointegration among the variables, which was as a result of similar outcome for the cointegration found among variables in the subgroups.

Table 5. Westerlund ECM Panel Cointegration test.

Test	Group Panel	UMIC	LMIC	LIC
Gt	−2.27 *	−2.73 **	−3.27 *	−1.57
Ga	−5.45	−7.02	−5.11	−5.19
Pt	−23.39 *	−5.26 **	−16.29 *	−4.69
Pa	−9.64 *	−6.61	−9.39 **	−3.80

*, ** indicate 1% and 5% significance level respectively. UMIC = Upper-middle income countries, LMIC = Low-middle income countries, LIC = Low income countries.

4.5. Hausman Test

Table 6 reports the results of Hausman test statistics for all the three predictor variable used in the study. The Hausman test statistics fail to decline the homogeneity of long-run coefficients because the chi2 value is greater than 0.05 in absolute value. Hence, the model supports the PMG estimator.

Table 6. Hausman Test.

	PMG	*MG*	*DFE*	*PMG/MG*	*PMG/DFE*
HIVPREV	1.12	3.18	0.23		
HCI	−10.08	−1.30	−0.75		
CLG	11.09	12.07	17.06		
Hausman Test				**−0.90**	**−5.75**

4.6. Long- and Short-Run Estimates

The analysis results from Table 7 indicate that when *ANS* is the dependent variable (Equation (1)), HIVPREV has a positive and significant long-run relationship with *ANS* at 1% significance level. However, when *HIVPREV* is the dependent variable (Equation (2)), *ANS* does not show any significant relationship with *HPREV*. This implies that the relationship between sustainable development and HIV/AIDS is unidirectional, which means that there is only effect running from *HIVPREV* to sustainable development, but not vice versa. Similarly, the relationship between human capital *(HCI)* and sustainable development is unidirectional. The results in Table 7 reveal a negative and significant relationship between the two variables. However, good governance (CLG) according to the estimate shows a positive and statistically significant long-run relationship with sustainable development.

Moreover, the results, as revealed in Table 7, show that HIV/AIDS has a negative and significant long-run relationship with human capital. It also worthy to note that the relationship is bidirectional. There is also a unidirectional long-run relationship between human capital and good governance. The result also established a bidirectional long-run relationship between HIV/AIDS and good governance. Meanwhile, all the results were supported with the estimates from the subgroup estimations. Table 8 shows the coefficients for the cointegration vectors for *ANS*, *HIVPREV, HCI,* and *CLG*, respectively. It is sufficient to say that the signs and intervals of *ECT*s from Table 8 are consistent with theory, meaning that a negative ECT ranges between 0 and 1 and is imperative for a stable error correction mechanism [54]. A positive *ECT* implies deviation from the equilibrium, while a negative ECT is important for the restoration of equilibrium following an exogenous shock.

Table 7. Long-run causality estimates.

		Independent Variables			
	Dep. Var.	**ΔANS**	**ΔHIVPREV**	**ΔHCI**	**ΔCLG**
Group Panel	ΔANS	-	1.12*(0.32)	−10.05**(4.28	11.11*(2.50)
	ΔHIVPREV	−0.001(0.004)	-	−23.11*(0.84)	2.12*(0.23)
	ΔHCI	0.0002(0.0002)	0.01**(0.002)	-	−0.05***(0.03)
	ΔCLG	0.001(0.001)	0.01**(0.01)	0.04(0.07)	-
UMIC	ΔANS	-	1.70**(0.77)	−7.33(7.85)	16.21***(9.17)
	ΔHIVPREV	−0.08**(0.04)	-	−26.81*(3.80)	1.85(2.81)
	ΔHCI	−0.003**(0.002)	−0.02*(0.006)	-	0.23***(0.13)
	ΔCLG	0.001(0.002)	−0.002(0.004)	−0.42*(0.07)	-
LMIC	ΔANS	-	−1.04(0.65)	37.06*(10.09)	22.41**(7.86)
	ΔHIVPREV	−0.004(0.01)	-	19.60*(4.99)	−8.96**(3.20)
	ΔHCI	0.001***(0.0003)	0.03**(0.01)	-	−0.11***(0.07)
	ΔCLG	0.001(0.001)	0.02***(0.01)	0.19(0.16)	-
LIC	ΔANS	-	1.24*(0.38)	−10.17***(5.72)	9.90*(2.75)
	ΔHIVPREV	0.08*(0.02)	-	0.67(0.69)	3.45*(0.75)
	ΔHCI	−0.02(0.01)	0.10(0.07)	-	−1.01***(0.60)
	ΔCLG	−0.001(0.003)	0.01(0.01)	0.10(0.10)	-

*, **, *** indicates 1%, 5% and 10% significance levels, respectively. Values in parentheses are standard error. UMIC = Upper-middle income countries, LMIC = Low-middle income countries, LIC = Low income countries.

Table 8. Short-run estimates (koint causality).

		Independent variables				
	Dep. Var.	**ΔANS**	**ΔHIVPREV**	**ΔHCI**	**ΔCLG**	**ECT(-1)**
Group Panel	ΔANS	-	9.82(10.16)	12.22(38.54)	0.94(3.04)	−0.50*
	ΔHIVPREV	0.001(0.002)	-	1.64(1.24)	−0.05(0.06)	−0.07*
	ΔHCI	0.0003(0.0003)	0.001(0.01)	-	0.01(0.01)	−0.05*
	ΔCLG	−0.0002(0.001)	0.06(0.07)	−0.25(0.70)	-	−0.36*
UMIC	ΔANS	-	−1.75(3.31)	37.96(62.63)	4.81(4.01)	−0.43**
	ΔHIVPREV	0.004(0.01)	-	−5.76***(3.10)	−0.15(0.19)	−0.10**
	ΔHCI	−0.000**(0.001)	−0.06***(0.04)		0.01(0.03)	−0.11*
	ΔCLG	−0.0001(0.002)	0.002(0.04)	0.10(0.37)	-	−0.62*
LMIC	ΔANS	-	38.28(33.90)	−66.22(41.21)	−5.98(8.06)	−0.53*
	ΔHIVPREV	0.0004(0.001)	-	2.19(3.82)	0.42(0.32)	−0.01
	ΔHCI	−0.0001(0.0001)	0.02(0.02)	-	0.02(0.02)	−0.07*
	ΔCLG	0.003(0.002)	0.17(0.13)	−1.19(1.25)	-	−0.49*
LIC	ΔANS	-	0.01(3.56)	39.80(55.81)	1.11(3.53)	−0.52*
	ΔHIVPREV	−0.003(0.002)	-	3.62**(1.62)	−0.04(0.08)	−0.03
	ΔHCI	0.001(0.001)	0.02(0.01)	-	0.01(0.01)	−0.01
	ΔCLG	−0.001(0.002)	0.0004(0.09)	0.09(1.09)	-	−0.25**

*, **, *** indicates 1%, 5% and 10% significance levels, respectively. Values in parentheses are standard error. UMIC = Upper-middle income countries, LMIC = Low-middle income countries, LIC = Low income countries.

The ECT coefficient from Table 8 shows that sustainable development, HIV/AIDS, human capital, and good governance can be restored to long-run equilibrium. The analysis of Equation (6), as presented in Table 7, indicates that there is long-run cointegration among the variables at 1% significance level, and the ECT coefficient of (–0.50) revealed in Table 8 implies that any deviation from the long-run equilibrium is corrected at 50% adjustment speed. This also indicates a strong and joint causality of the three variables on sustainable development.

From Tables 7 and 8 and Equation (7), the results show a long-run cointegration among the variables at 1% significance level. The results also reveal a strong and joint causality of sustainable development, HIV/AIDS prevalence, and good governance on human capital. Human capital could be significantly restored to its long-run equilibrium at 5% adjustment speed in the presence of a shock. Analysis for Equation (8), as presented in Table 8, indicates that sustainable development, human capital, and good governance have a joint causal effect on HIV/AIDS prevalence, while Table 7 reveals that there is long-run cointegration which is statistically significant at 1% level. In presence of a shock, *HIV/AIDS* could be significantly restored to its long-run equilibrium at 7% adjustment speed. Similarly, in reference to Equation (9), sustainable development, HIV/AIDS prevalence, and human capital have a joint and strong causal effect on good governance, which is depicted in Table 8. In case of any shock in the system, it could be adjusted at 36% adjustment speed.

For upper-middle income economies, a long-run bidirectional causal relationship was found to exist between sustainable development and HIV/AIDS and human capital, and sustainable development and country-level governance. Meanwhile, a unidirectional long-run causal relationship was found to exist between human capital and country-level governance, and human capital and sustainable development. However, a bidirectional short-run causality was found between HIV/AIDS and human capital, and a unidirectional short-run causality was found between sustainable development and human capital.

As for the joint causality, the results are summarized in Table 8. The results show that HIV/AIDS, country-level governance, and human capital have joint causality on sustainable development. The model has about 43% speed of adjustment to return back to equilibrium in the presence of shock. Similarly, sustainable development, human capital, and country-level governance show a strong joint causality on HIV/AIDS with 10% speed of adjustment. HIV/AIDS, country-level governance, and sustainable development were found to have a strong joint causal long-run relationship on human capital, while HIV/AIDS, sustainable development, and human capital were also found to have a strong long-run causal relationship with country-level governance.

In a similar result to that obtained with respect to the group panel, we found bidirectional long-run causal relationship between HIV/AIDS and human capital, sustainable development and human capital, and HIV/AIDS and country-level governance. A unidirectional long-run causal relationship was found between human capital and country-level governance, and sustainable development and country-level governance. The results are presented in Table 7. Further estimates, as shown in Table 8, reveal that HIV/AIDS, country-level governance, and human capital were found to have joint long-run causal relationship with sustainable development. Sustainable development, HIV/AIDS, and human capital also have a joint long-run causal relationship with country-level governance.

As for the low income economies, the results as shown in Tables 7 and 8 are not significantly different from the other three panesl. As summarized in Table 7, a bidirectional long-run causal relationship was found to exist between sustainable development and HIV/AIDS, while a unidirectional relationship was found to exist between sustainable development and human capital, human capital and country-level governance, country-level governance and HIV/AIDS, and country-level governance and sustainable development. Meanwhile, a joint long-run causal relationship was found between country-level governance, HIV/AIDS, and human capital on sustainable development, and between sustainable developments, HIV/AIDS, and human capital on country-level governance (Table 8).

4.7. Robustness Check

We considered dividing the group panel into subgroups (upper-middle income, low-middle income, and low income countries) for analysis using PMG estimator. The results are summarized in Tables 7 and 8. First, we estimated the cointegration across the subgroup. The results, as presented in Table 5, supported our findings for the whole group panel that a long-run relationship exists among the sustainable development (ANS) and the variables considered. Meanwhile, the short-run relationship varies across the subgroups (Table 8). Human capital was found to have a short-run negative causal relationship with HIV/AIDS prevalence in upper-middle income countries (UMIC), while it was positive for low income countries (LIC). However, it has no short-run relationship in low-middle income countries (LMIC), which is similar to the results obtained for the group panel.

5. Summary and Conclusion

This study empirically examined the relationship among sustainable development, HIV/AIDS prevalence, human capital, and good governance in 26 sub-Saharan Africa countries using dynamic heterogeneous panel estimation. In the present globalized era, the issue of sustainable development is critical to measure the progress of any country's development, which will not only account for the economic development, but other factors that will account for the general improved welfare of the citizen. It has become essential to understand the underlying fundamental factors that influence the achievement of sustainable development in the region. Thus, variables like HIV/AIDS, which have been a great challenge to Africa countries, human capital, and country-level governance are taken as the independent variables, which are measured using yearly data from 1990 to 2016 and were analyzed using pooled mean group estimator. To ensure the robustness of the findings, the panel was subdivided into three panels based on the World Bank level of economies categorization. The three categories are upper-middle income (UMIC), low-middle income (LMIC), and low income (LIC) countries.

For the group panel, a bidirectional long-run causal relationship was found between HIV/AIDS and human capital, and HIV/AIDS prevalence and country-level governance. A unidirectional long-run causal relationship was found to exist between human capital and country-level governance, while a bidirectional long-run causal relationship was found between sustainable development and country-level governance, human capital, and sustainable development, and sustainable development and HIV/AIDS.

The positive and significant long-run causal relationship between HIV/AIDS and sustainable development is in line with some previous studies [19,24], which argued that in the future, HIV/AIDS is not likely to threaten economic growth in Africa. Sustainable development and good governance according to the estimated results reveal a positive and significant long-run relationship. This result is in line with previous studies. Previous studies found that the central place of development policy is occupied with the model of good governance [7,31–33], which has become the cornerstone of sustainable development. However, the result is in contrast to some previous studies [34,35], which found no relationship between sustainable development and good governance. The result from the estimates implies that to achieve sustainable development in sub-Saharan Africa countries, there is a need for a concerted effort on the part of the continent country's government to ensure effective good governance. However, while a unidirectional long-run causal relationship was found between sustainable development and HIV/AIDS in the group panel, a bidirectional long-run causal relationship was found between sustainable development and HIV/AIDS in UMIC and LIC respectively. The difference could be attributed to the heterogeneous nature of the countries included in the panel.

A disturbing result from the study is the coefficient sign of a human capital long-run relationship with sustainable development. The authors hypothesized a positive relationship, but the result turned out to be negative, although the significant long-run relationship found in this study is in line with some authors, who inferred human capital to have a significant long-run relationship with the sustainable development of any country [37–40]. However, the negative sign of the result is not surprising in reference to the study of Quadri and Waheed [56], who observed that the contribution of human capital to sustainable development is more in the theoretical realm than the empirical. The study submitted that the theoretical contribution of human capital is clear, but empirical findings are mixed [56]. An interesting finding from this study is the significant strong joint causality of sustainable development, good governance, and human capital on HIV/AIDS prevalence, and in case of any shock, it could be restored back to equilibrium at 7% adjustment speed. This is an indication that, the threat of HIV/AIDS prevalence on sustainable development could be curtailed by putting effective policies and programs in place. There is also a bi-directional long-run relationship between HIV/AIDS prevalence and good governance. It is of importance to note that in sub-Saharan Africa countries, an effective good governance would enhance significant reduction in the prevalence of HIV/AIDS in the region.

The study estimated the relationship among sustainable development, HIV/AIDS prevalence, human capital, and good governance. It found that all the variables are cointegrated, which implies a long-run relationship. The estimation of the long-run slope coefficient restricted it to be homogenous across countries. This is because the authors expect that the long-run equilibrium relationship between the variables will be similar across countries in sub-Saharan Africa. Future studies can do a comparative study of countries with high HIV/AIDS prevalence in African regions to confirm the outcome of these results. Also, there is a need for a robustness test to explore the mixed result on the relationship between sustainable development and human capital. Based on the findings of this study, it is imperative for the government and stakeholders in the region to pursue policies that will enhance sustainable development with expected long-term results, rather than short-term gains. First, there is a need to improve the country-level governance policy, development of human capital, and improve on the policies and programs targeted toward the prevention and eradication of HIV/AIDS in sub-Saharan Africa countries. Second, human capital needs to be more developed to drive down the effects of HIV/AIDS prevalence. Lastly, good governance, found to have a long-run relationship with sustainable development, should be strengthened to ensure that the rule of law prevailed, transparency in their dealings, corruption to be eradicated, conducive business regulatory environment, and a country free of war/terrorism. However, sustainable development is achievable in sub-Saharan Africa countries if an adequate research grounded policy is put in place to address the challenges as revealed by this study.

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Appendix A

Table A1. List of countries in the panel.

S/No	Country	Classification	S/No	Country	Classification
1	Angola	LMIC	14	Madagascar	LIC
2	Benin	LIC	15	Malawi	LIC
3	Bostwana	UMIC	16	Mali	LIC
4	B/Faso	LIC	17	Mauritania	LMIC
5	Burundi	LIC	18	Mozambique	LIC
6	Cameroon	LMIC	19	Namibia	UMIC
7	Congo DR	LIC	20	Niger	LIC
8	Congo R	LMIC	21	Nigeria	LMIC
9	C/Ivoire	LMIC	22	Senegal	LIC
10	Eswatini	LMIC	23	S/Leone	LIC
11	Gabon	UMIC	24	S/Africa	UMIC
12	Gambia	LIC	25	Togo	LIC
13	Ghana	LMIC	26	Uganda	LIC

UMIC = Upper-middle income countries, LMIC = Low-middle income countries, LIC = Low income countries.

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The Impact of Market Condition and Policy Change on the Sustainability of Intra-Industry Information Diffusion in China

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Abstract: Through an investigation into seven major industries in China's stock market from 2002 to 2013, this study focuses on two main external determinants: market condition and policy change on intra-industry information diffusion. We employ both time-series and panel Vector Auto-regression (VAR) methods on a sample data of 1175 firms for the analysis. The investigation reveals that market conditions and policy changes affect the process of intra-industry information diffusion in China. The speed of intra-industry information diffusion in a down-market state is slower than an upmarket, especially when the evidence is more significant in the longer horizon of the market condition. Policy changes, especially the split-share structure reform, impede the process of intra-industry information diffusion. The investigation outcome also reveals that there is an increasing delay in intra-industry information diffusion over time in China's stock market after 2005. However, because of the decreasing information volatility of intra-industry information diffusion, policy changes are useful to a certain extent.

Keywords: market condition; policy change; information diffusion; intra-industry; China

1. Introduction

Under the Efficient Market Hypothesis (EMH), information diffuses without any delay in a complete and frictionless market. However, ever since the seminal work of Lo and MacKinlay [1], researchers increasingly discover that information gradually diffuses in the realistic market. From research views to research methods, an abundance of researchers continually explore the study of gradual information diffusion [2–7]. Many past studies contribute internal determinants, such as the firm's characteristics in the process of information diffusion [8–10].

Additionally, external factors that could affect the process of information diffusion have also been explored. Two potential external determinants that can affect information diffusion are market condition and policy change. Certain literatures focus on market condition to explore information diffusion. For example, McQueen et al. [11] and Chang et al. [12] suggest that, by reason of small stocks' lagged response in up market, gradual information diffusion is more significant in up market rather than down market. In contrary to McQueen et al. [11], Hameed and Kusnadi [3] claim that the speed of information diffusion is supposed to be slower when the market falls. Chen & Rhee [13] suggest that both short sale and market conditions could affect the speed of information diffusion.

They argue that the speeds of information diffusion are similar in the both up and down markets. Therefore, the market condition that can delay the diffusion of information seems be controversial.

Another external determinant is policy change. As an important setting in a market environment, policy change has significant impact on the financial market from various aspects and the influence on information diffusion is just a sub-fraction. It is the process of gradual discovery. Any policy change is not always smooth and successful and the market environment and institutional arrangement can be responsible for the speed of information diffusion. Merton [14] recognizes the importance of institutional constraints in the information achievement and diffusion procedure. In recent years, the impact of policy changes on financial markets has become one of the more recent research hotspots. Theoretically and empirically, the importance of a variety of policies and environmental changes on the process of information diffusion is explored by several researchers. Lin & Swanson [15] argue that policy changes in China could influence the China segmented stock market more. They suggest that the policy changes alleviate barriers of information diffusion. In addition, Bae et al. [16] argue that the policy of liberalization of stock market produces more information on the efficiency of stock prices for emerging markets. They discover that foreign investors can facilitate the diffusion of global market information into stock prices. On the other hand, Mori [17] investigates how policy and environmental changes in the Real Estate Investment The trust market could affect the process of information diffusion in the United States (U.S.) market. He discovers that changes of the process of information diffusion depend on both different government policies and changes of firm size.

On the other hand, most of the previous studies investigate the process of information diffusion based on the whole market and, by narrowing the research scope, a few researches have also examined information diffusion that relates to industries such as customer-supplier and upstream-downstream industries [5,6,18]. However, researches rarely focus on firms within an industry to investigate the process of information diffusion. Cen et al. [19] report that industry-wide information is first incorporated into the stock prices of industry leaders who are more liquid and have high level of analyst coverage, and then the information gradually distributes to other industry followers. Importantly, Hou [4] particularly examines the intra-industry information diffusion. He argues that gradual information diffusion mainly exists in intra-industry rather than cross-industry or outside-industry. Haque [20] further support the hypotheses of Hou [4] with data in Australia. However, they only focus on the internal impact factors of intra-industry information diffusion. External determinants of intra-industry information diffusion have not been adequately touched on in their researches.

By including the market conditions and policy changes, this study stresses the roles of external determinants on intra-industry information diffusion in China's stock market. To the best of our knowledge, this study is the first of its kind, which focuses on the intra-industry to investigate the process of information diffusion with views of market conditions and policy changes. The research not only focuses on individual industries, but it also processes a major investigation of intra-industry. The findings of this research contribute to the pool of existing literature in several ways. First, as an external determinant, how market conditions affect information diffusion in the stock market is still controversial. Moreover, the research scope focuses on intra-industry. This study is the first attempt to explore the impact of market condition on information diffusion with focus on intra-industry.

Second, as the largest emerging market, China's stock market has unique microstructures and institutional arrangement, which are different with most developed markets. Due to the relatively shorter development period, China's stock market suffers from market immaturity and investors irrationality. With the specific conditions in China, the study focuses on whether and how policy changes influence the process of intra-industry information diffusion. Institutional frictions are accountable for producing the delay in the process of information diffusion. Thus, comprehending the process of information diffusion is very important for policy considerations. Institutional reforms in China's stock market have been implemented for many years since the establishment of the market. However, the effectiveness of the changes in policy is still in dispute. Whether policy reforms are effective in China stock market? Whether China government can professionally regular and controls the market? How to smooth the process of information diffusion and increase informativeness of stock price? How do investors make use of information? These problems always puzzle government authorities and investors. Therefore, revolving around intra-industry information diffusion, further systematic investigation and exploration are necessary. Policy considerations and market mechanisms in China should keep pace with the times, which could, in turn, ensure that stock prices develop more effectively and informatively. Based on the most important policy changes, i.e., the split-share structure reform in 2005 and lifting short-sale constraints in 2010, this study is the first to investigate the impact of policy change on intra-industry information diffusion. Consequently, this study provides several evidences to help the government authorities in smoothing the process of intra-industry information diffusion and augmenting the market efficiency.

Third, the study focuses on China's stock market. As the biggest emerging market, research on China's stock market is a significant reference for investigation into other emerging markets. Most researches about information diffusion in China concentrate on the whole market [7,21] or segmented markets, such as A-share and B-share [15,22]. As far as we know, no literature focuses on intra-industry to investigate information diffusion in China's stock market. Based on the main intra-industry analysis, the study fills the gap.

The organization of the paper is stated, as follows: Section 2 discusses policy changes in China's stock market; Section 3 shows the data and main methods, whereas the impact of market condition on intra-industry information diffusion is examined in Section 4; Section 5 presents the impact of policy changes on the process of intra-industry information diffusion; and, the conclusion and discussion are described in Section 6.

2. Policy Changes in China's Stock Market

Since the reform and opening in 1978, China has experienced a fast transformation from the planned economy to market economy at the national level. Over the past three decades, China has gone through impressive economic growth and turned into the world's second largest economy. It became a member of the World Trade Organization (WTO) that is recognized as one of the BRICs (Brazil Russia India China) by international investment banks (Goldman Sachs) in 2001. Due to its fast economic development and enormous growth opportunities in China, as an indispensable part of the Chinese economy, China's stock market increasingly attracts domestic and foreign investors' attention. As an emerging market, China's stock market has the second largest trading volume, as well as the second largest market capitalization of $6.4 trillion in 2014 [23], only after the U.S. China's stock market became one of the most active markets based on the number of listed companies, the total trading volume, the market capitalization, participation of foreign investors, and the unique categorization of stocks. Therefore, a considerable amount of investment interests and academic attention around the world concentrate on China's stock market.

Notwithstanding its fast development and emerging importance, China's stock market may suffer from market irrationality and excessive fluctuation. Therefore, China's government has to continuously regulate and control the market, as well as stabilize its stock prices. However, the regulation effects are always met with skepticism. For the last ten years, among all of the policies, two policies are the most significant and they show the greatest impact to China's stock market. First, the split-share structure reform that happened in 2005. Based on the tradability, the stocks of listed companies can be put into two major classes: tradable stocks and non-tradable stocks. More specifically, non-tradable stocks belong to all levels of government or government-controlled financial institutions. Wu [24] argues that the issuance of non-tradable stocks increases the inefficiency of China's stock market. For example, less tradable stocks can bring about a decrease in liquidity and they are convenient to the practice of insider information trading.

On the other hand, tradable stocks can be freely traded by individual, as well as institutional investors. All companies have non-tradable shares in varying proportions. Before 2005, non-tradable shares contain about two-thirds of the total number of outstanding shares. An excess of non-tradable shares in the stock market bring out several problems for further development of the market. In April 2005, the China Securities Regulatory Commission (CSRC) initiated the reform of non-tradable shares, i.e., the split-share structure reform, trying to transfer all non-tradable shares into tradable shares. The central focus of the split-share structure reform is that holders of non-tradable shares are obliged to compensate the holders of tradable shares in order to obtain the liquidity rights for the option to sell their shares in the future [25]. The potential impact of the split-share structure reform has been discussed by a few empirical literatures. Li et al. [26] suggest that the split-share structure reform might be the most powerful policy reform of China's stock market in recent years. Beltratti et al. [25] discuss that this reform lays down the conditions for essential future changes in ownership, liquidity, and corporate governance in China. However, Carpenter et al. [27] suggest that the split-share structure reform has only little direct immediate impact on the structure of China's stock market in the short term.

The second important policy is lifting short-sale constraints. Before 2010, there were strict short-sale constraints in China's stock market. Under short-sale constraints, due to the ban of law, investors are unable to freely short-sell stocks that they do not hold. Theoretically, short-sale constraints could affect the process of information diffusion. Diamond and Verrecchia [28] maintain that short-sale constraints could delay new information that is to be incorporated into stock prices. Negative information also has difficulties in incorporating stock price and diffusing slowly. In order to improve the process of China's financial market marketization, as well as acting on international convention, CSRC finally abolished the short-sale constraints of China's stock market in February 2010. Therefore, after 2010, after short-sale constraints disappeared, market transactions might have further development room. Chang et al. [29] report that Chinese investors seemed to be unfamiliar with the short-sale mechanism and it is deemed that many of them choose to keep away from short-sales. However, Zhao et al. [30] argue that permitting short-sales could decrease market volatility and provide more suitable stock return allocation in China's stock market. As a result, China's stock market provides appropriate areas to investigate the process of information diffusion with or without short-sale constraints.

3. Data and Methodology

3.1. Data

China's stock market was established in the early 1990s, and in the initial ten years, stock prices fluctuated excessively. CSRC is obliged to continuously introduce policies to stabilize the market. For the purpose of obtaining a relatively stable period of China's stock market, we exclude the initial years since its establishment. Hence, the study period will be from January 2002 to December 2013.

It also focuses on the investigation of intra-industry in China's stock market, because the number of industry is relatively larger. There are 38 industries in China's stock market in the present. However, the number of firms within the industry varies in different industries. Some have more than 100 firms, while some industries only have a few. Sufficient research data is necessary to support the research objectives of this study. The industry that had the number of firms greater than 80 is chosen. (Hou [4] chooses the industry in the U.S. market with the number of firms that are greater than 80. This is a better reference. Not only that, the number of firms in each portfolio should be enough for analysis. Examining information diffusion within an industry in the Australian market, Haque [20] chooses industries that have five to 26 firms. Thus, the number of firms in each portfolio is only two to seven. Due to a smaller firm number, it is difficult to not suspect the validity of the results. Consequently, we chose the industry where the number of firms is greater.) However, the number of firms constantly changes every year. Therefore, to be more specific, we chose the industry with more than 80 firms in 2013. In addition, major industries in China also required selection to guarantee the comprehensiveness of the study. Consequently, we chose the industry with a number of firms greater than 80 and consider this to be a major industry in China. As a result, we chose seven industries and 1175 firms to be the sample in this study. Table 1 shows the number of firms in the sample industries.

Table 1. Number of Firms in Sample Industries.

Industry	Number of Firms
Automobiles parts	127
Construction and materials	202
Food producers	95
Electronic equipment	126
Industrial engineering	230
Industrial metals and mining	234
Pharmaceuticals and biotechnology	161

In order to avoid the considerable bias that is connected with nonsynchronous trading and some microstructure effects at the daily level, weekly returns rather than daily returns are employed in our paper. In addition, seasonal patterns might affect weekly autocorrelations of stock returns [31]. Hou [4] argues that, based on five trading days, if Friday is close, then the autocorrelations of the corresponding weekly return should be higher. On the other hand, if Tuesday is closed, then the autocorrelations of the corresponding weekly return should be smaller. Thus, if Wednesday is closed, then the autocorrelations of the corresponding weekly return should be in between. Using this finding, we estimate the weekly returns from Wednesday close to the subsequent Wednesday close. If the following Wednesday is not a trading day, it will be extended to the next trading day. This method of calculating weekly returns is commonly used in the literature, see, for example, Hameed and Kusnadi [3], and Hou [4]. Nevertheless, Chordia and Swaminathan [10] and Haque [20] employ both the weekly data and daily data to run the Vector Auto-regression (VAR) model. They find that the result of weekly data and the result of daily data are similar.

3.2. Descriptive Statistics

In order to avoid the impact of non-synchronous trading and microstructure effects, many studies use weekly and size-based portfolio data [3,4]. Following the same scenario, the empirical investigation is processed on a weekly and size-based portfolio return.

The size portfolios within the industry are formed, ranking all the firms based on their market capitalization i.e., total capital in the December of each year. The firms are divided into three portfolios: bottom 30%, middle 40%, and top 30%. Portfolio S denotes the smallest 30% firms and portfolio B includes the largest 30% firms. The equal-weighted portfolio weekly returns for each size-ranked portfolio are estimated. R_B and R_S are the weekly returns of the biggest and smallest size portfolios, respectively. Before the empirical analysis is presented, necessary descriptive statistics are essential. More specific descriptive statistics are stated in Table 2:

Table 2 displays the descriptive statistics for the largest and smallest 30% size portfolios of all sample industries from 2002 to 2013. There are 626 weekly returns in each industry-size portfolio. The average weekly returns of the smallest 30% firms are obviously greater than the average weekly returns of the largest 30% firms. Therefore, small firms usually obtain a higher average return, which is consistent with previous studies on size premium [32–35]. Moreover, the standard deviation of the smallest 30% firms' return is always greater than the standard deviation of the largest 30% firms' return. These results imply that the small firm poses higher risk with regards to higher returns. Kurtosis in each portfolio is greater than three, while the skewness in each portfolio is closed to zero. Furthermore, the unit root test is generally employed to examine the stationary of the time-series data. As shown in Table 2, the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests reject the null hypothesis at 1% level in all industries, which exhibited that the data has no root unit. The results displayed in these returns are stationary.

Table 3 describes the results from the first through fourth order autocorrelations and cross-autocorrelations of the largest 30% firms and the smallest 30% firms in each industry. The first-order autocorrelation coefficient declines as we move from the smallest firms to the largest.

The longer it lags, from two to four weeks, the autocorrelation functions decline faster. Second, for most industries, the correlation coefficient between the returns on the lagged largest 30% firms and the current smallest 30% firms is greater than the correlation coefficient between returns on the lagged smallest 30% firms and the current largest 30% firms. Table 3 also shows that the cross-autocorrelations decay in most industries, as more lags come. Therefore, the cross-autocorrelations show that the big firms' lagged returns provide predictive ability for smaller firms' current returns. Consequently, the lead-lag effect between the big and small firms is evidently displayed within the industry. Furthermore, these asymmetric cross-autocorrelations are consistent with the hypothesis of gradual information diffusion: when new information comes, small firms react more slowly than big firms.

Table 2. Descriptive Statistics for the weekly return of Intra-industry Portfolios.

Industry Portfolio	Mean	Std	Median	Max	Min	Kurtosis	Skewness	ADF Test	PP Test
Auto-big	0.0005	0.048	−0.0005	0.1580	−0.1866	4.2936	−0.0812	−14.969 ***	−25.490 ***
Auto-small	0.00056	0.051	0.0026	0.1481	−0.2524	5.0236	−0.5042	−23.492 ***	−23.614 ***
Cons-big	0.0002	0.047	0.0006	0.1523	−0.2028	4.5305	−0.2174	−15.479 ***	−25.159 ***
Cons-small	0.0009	0.052	0.0048	0.1601	−0.3004	5.5341	−0.5967	−24.146 ***	−24.158 ***
Elec-big	0.0003	0.047	0.0015	0.1822	−0.1893	4.2391	−0.1793	−25.130 ***	−25.129 ***
Elec-small	0.0014	0.051	0.0056	0.1535	−0.2241	4.9526	−0.4652	−24.822 ***	−24.823 ***
Food-big	0.0006	0.046	0.0024	0.1414	−0.2388	4.5246	−0.1952	−24.630 ***	−24.630 ***
Food-small	0.0009	0.049	0.0036	0.1931	0.2543	5.4559	−0.4885	−24.121 ***	−24.172 ***
Engi-big	0.0001	0.049	6.82E-05	0.1608	−0.1982	4.2426	−0.0678	−24.940 ***	−24.947 ***
Engi-small	0.0012	0.051	0.0040	0.1498	−0.2764	5.4045	-0.5923	−24.221 ***	−24.279 ***
Meta-big	−0.0006	0.049	−0.0024	0.1793	−0.1796	4.4632	−0.0823	−15.329 ***	−24.292 ***
Meta-small	0.0010	0.051	0.0034	0.1380	−0.2672	4.8873	−0.4950	−14.906 ***	−23.702 ***
Phar-big	0.0014	0.042	0.0040	0.1656	−0.1710	4.7004	−0.0728	−15.413 ***	−25.626 ***
Phar-small	0.0017	0.049	0.0039	0.1497	−0.2486	5.2476	−0.5787	−15.234 ***	−24.081 ***

Notes: Auto-big and Auto-small refer to the largest 30% size portfolio and the smallest 30% size portfolio in Automobiles parts industry, respectively. Similarly, Cons-big and Cons-small, Elec-big and Elec-small, Food-big and Food-big, Engi-big and Engi-small, Meta-big and Meta-small, and Phar-big and Phar-small refer to the largest 30% size portfolio and the smallest 30% size portfolio in Construction and materials industry, Electronic equipment industry, Food producer industry, Industrial engineering industry, Industrial metals and mining industry, andPharmaceuticals and biotechnology industry, correspondingly. N denotes the average number of firms in each portfolio from 2002 to 2013. Finally, ***, **, and * denote the significance at the 1, 5, and 10 % levels, respectively.

Table 3. Autocorrelation Matrices.

Industry Portfolio	ρ_0(j,B)	ρ_0(j,S)	ρ_1(j,B)	ρ_1(j,S)	ρ_2(j,B)	ρ_2(j,S)	ρ_3(j,B)	ρ_3(j,S)	ρ_4(j,B)	ρ_4(j,S)
Auto-big	1	0.814	−0.029	−0.082	0.163	0.053	0.065	−0.049	−0.038	−0.013
Auto-small	0.913	1	0.083	0.034	−0.045	0.074	0.057	0.060	0.017	−0.049
Cons-big	1	0.831	−0.022	−0.062	0.134	0.045	0.071	−0.034	−0.083	0.010
Cons-small	0.974	1	0.086	0.016	−0.044	0.069	0.041	0.054	−0.011	−0.089
Elec-big	1	0.869	−0.023	−0.026	0.113	−0.001	−0.002	−0.032	−0.123	−0.043
Elec-small	0.988	1	0.032	−0.015	−0.002	0.093	0.040	0.034	0.045	−0.051
Food-big	1	0.876	−0.003	−0.037	0.095	0.009	0.061	−0.006	−0.103	0.010
Food-small	0.977	1	0.035	0.022	−0.002	0.075	0.021	0.067	−0.135	−0.096
Engi-big	1	0.854	−0.016	−0.069	0.116	0.034	0.091	−0.004	−0.113	−0.014
Engi-small	0.911	1	0.047	0.003	−0.025	0.090	0.008	0.050	0.023	−0.063
Meta-big	1	0.819	0.020	−0.049	0.122	0.042	0.058	−0.033	−0.091	−0.022
Meta-small	0.863	1	0.064	0.037	−0.014	0.129	0.027	0.055	0.022	−0.084
Phar-big	1	0.753	−0.039	−0.076	0.148	0.035	0.053	−0.003	−0.097	−0.016
Phar-small	0.991	1	0.083	0.018	−0.029	0.116	0.003	0.020	0.005	−0.058

Notes: ρ_m(j,k), m = 0 to 4, j = B or S, and k = B or S, is correlation coefficient. B and S refer to the largest 30% size portfolio and the smallest 30% size portfolio, respectively. ρ_m(j,k) refers to the m^{th} order correlation coefficient between returns on the largest 30% size portfolio and the smallest 30% size portfolio. For example, ρ1(S, B) denotes the correlation between week t return on the smallest 30% size portfolio and week t−1 return on the largest 30% size portfolio. ρ2 (B, S) represents the correlation between week t return on the largest 30% size portfolio and week t−2 return on the smallest 30% size portfolio. On the other hand, ρ_m(j,k) also displays autocorrelation of portfolios' return. For instance, ρ1 (B, B) refers to the first-order autocorrelation of the largest 30% size portfolio. ρ4 (S, S) means the fourth-order autocorrelation of the smallest 30% size portfolio.

3.3. Vector Auto-regression (VAR)

According to the hypothesis of time-varying expected returns, the cross-autocorrelations between the big firms' lagged returns and the small firms' current returns are caused by a combination of small firms' high autocorrelations and a high contemporaneous correlation between the big and small firms [31,36] Moreover, the contemporaneous correlation coefficients between the small and the big firms are always greater than 0.7 in all sample industries. These results imply that high contemporaneous correlation also appear between the small and big firms. Thus, vector-autoregressive regression (VAR) tests are employed to control the autocorrelations of small firms and the contemporaneous correlation between big and small firms. Brennan et al. [8] first employ the VAR model to investigate the process of intra-industry information diffusion. They conclude that, when there is only lagged impact rather than contemporaneous impact among variables, it is suitable to set up the VAR procedure. They further propose that error term actually implies contemporaneous impact. Chordia and Swaminathan [10] state that the VAR model not only prove whether big firms' lagged returns lead small firms' current returns, but more importantly, it could provide a kind of measure about the speed of information diffusion. The corresponding VAR model for each respective industry is described in the following equations:

$$\mathrm{R_{S,t}} = a_0 + \sum_{k=1}^{K} a_k R_{S,t-k} + \sum_{k=1}^{K} b_k R_{B,t-k} + u_t \tag{1}$$

$$\mathrm{R_{B,t}} = c_0 + \sum_{k=1}^{K} c_k R_{S,t-k} + \sum_{k=1}^{K} d_k R_{B,t-k} + v_t \tag{2}$$

Furthermore, by combining all the sample firms, regardless of the industry, a panel VAR model to process the entire investigation of intra-industry is also built:

$$\mathrm{R_{S,i(t)}} = a_{i,0} + \sum_{k=1}^{K} a_k R_{S,i(t-k)} + \sum_{k=1}^{K} b_k R_{B,i(t-k)} + u_{i,t} \tag{3}$$

$$\mathrm{R_{B,i(t)}} = c_{i,0} + \sum_{k=1}^{K} c_k R_{S,i(t-k)} + \sum_{k=1}^{K} d_k R_{B,i(t-k)} + v_{i,t} \tag{4}$$

In Equations (1) and (2), $\mathrm{R_{S,t}}$ and $\mathrm{R_{S,t\text{-}k}}$ are the equal-weighted weekly returns on the smallest 30% portfolio at period t and period t-k, while $\mathrm{R_{B,t}}$ and $\mathrm{R_{B,t\text{-}k}}$ present the equal-weighted weekly return on the largest 30% portfolio at period t and period t-k. (We obtain similar results using value-weighted weekly returns, results are available upon request.) On the other hand, in Equations (3) and (4), $\mathrm{R_{S,i}}$(t) and $\mathrm{R_{S,i}}$(t-k) are the equal-weighted weekly returns on the smallest 30% portfolio at period t and period t-k in industry i, while $\mathrm{R_{B,i}}$(t) and $\mathrm{R_{B,i}}$(t-k) present the equal-weighted weekly return on the largest 30% portfolio at period t and period t-k in industry i. Moreover, in Equations (1) and (3), a_k and b_k are the coefficients of the lagged returns of $\mathrm{R_S}$ and $\mathrm{R_B}$, respectively. In Equations (2) and (4), $\mathrm{c_k}$ and $\mathrm{d_k}$ are the coefficients of lagged returns of $\mathrm{R_S}$ and $\mathrm{R_B}$, respectively. a_0 and c_0 ($a_{i,0}$ and $\mathrm{c}_{i,0}$) are the constant terms, correspondingly. Finally, u_t and v_t ($u_{i,t}$ and $\mathrm{v}_{i,t}$) are the error terms, respectively.

In the above time-series and panel VAR settings, $\sum_{k=1}^{K} a_K$ and $\sum_{k=1}^{K} d_K$ denote the degree of the autocorrelations of small and big firms, respectively. $\sum_{k=1}^{K} b_K$ and $\sum_{k=1}^{K} c_K$ refer to the impact of lagged big firms' returns on current small firms' returns, as well as the impact of lagged small firms' returns on current big firms' returns correspondingly. If there is lead-lag relation between the big and small firms, which is generated by gradual information diffusion, the sum of coefficients $\sum_{k=1}^{K} b_K \geq 0$ is expected. Furthermore, according to Brennan et al. [8], we could employ the cross-equation test for null hypothesis: $\sum_{k=1}^{K} b_K = \sum_{k=1}^{K} c_K$ to check whether one portfolio's lagged return can predict another portfolio's current return. If the lead-lag relation is driven by a gradual diffusion of information from big firms to small firms, we expect $\sum_{k=1}^{K} b_K > \sum_{k=1}^{K} c_K$. (We estimate the VAR for the full sample period and find the impact of lagged big firms' returns on current small firms' returns is significantly greater than the impact of lagged small firms' returns on current big firms' returns. The results suggest the existence of the significantly gradual intra-industry information diffusion in China's stock market, by means of a significant intra-industry lead-lag relationship between big stocks' lagged returns and small stocks' current returns. The empirical results are available upon request.) Additionally, we also exclude the effect of cross-industry information diffusion in this study. The gradual information diffusion between big and small firms only appears within the industry, rather than across the different industries. (We confirm the gradual information diffusion actually is intra-industry information diffusion.)

4. Market Conditions and Intra-Industry Information Diffusion

To explore the impact of market conditions, they are categorized as up or down, depending on whether the previous market return is positive or negative. According to Hameed and Kusnadi [3], the period definition of market conditions might affect the impact of market condition on cross-autocorrelations. There is no theoretical guide on period definitions regarding up and down markets, as it depends on the research objectives and sample markets. Some studies employ longer period definitions of market conditions. For example, both Cooper et al. [33] and Wu [24] employ 36-month market returns as the definition of market conditions in order to examine momentum strategy in the U.S. and China markets. However, some of the studies use shorter period definitions of market conditions. For instance, in examining the lead lag effect in the Warsaw's stock market, Gębka [37] defines market conditions using daily market return. In the U.S. and six Asia markets, McQueen et al. [11] and Chang et al. [12] employ a month's market return as the proxy of up and down markets to examine the cross-autocorrelation of stock returns.

Therefore, we employ four weeks to be the shorter horizon of the market condition. On the other hand, to comprehensively investigate the impact of market conditions on the process of intra-industry information diffusion, longer period definitions of market conditions should also be considered. Meanwhile, due to excessive volatility in China's stock market, periods that are too long have difficulties reflecting the fluctuations in market returns. Therefore, we employ 26 weeks to be the longer horizon of market condition in this study. (Hameed and Kusnadi [3] examine information diffusion and market conditions in the Japan market using both shorter and longer period definitions. They define the previous four or 26 weeks to determine market conditions.) As a result, by employing shorter and longer standards of period definitions, we define the previous four and 26 weeks to respectively establish the market conditions. (We obtain similar results using other period definitions, such as the previous 12 weeks, to determine market conditions; the results are available upon request.)

Consequently, if the previous four-week or 26-week market return is positive, the market condition can be confirmed as the up market state, or otherwise the down market state. Our main objective is to investigate the impact of market conditions on intra-industry information diffusion. To test this objective, two dummy variables, i.e., $D_{\text{up,t-k}}$ and $D_{\text{down,t-k}}$, are added into the original VAR model. Particularly, the new conditional VAR model is stated in the following equations:

$$R_{S,t} = a_0 + \sum_{k=1}^{K} a_{k,up} R_{s,t-k} \cdot D_{up,t-k} + \sum_{k=1}^{K} b_{k,up} R_{B,t-k} \cdot D_{up,t-k} + \sum_{k=1}^{K} a_{k,down} R_{s,t-k} \cdot D_{down,t-k} + \sum_{k=1}^{K} b_{k,down} R_{B,t-k} \cdot D_{down,t-k} + u_t \quad (5)$$

$$R_{B,t} = a_0 + \sum_{k=1}^{K} c_{k,up} R_{s,t-k} \cdot D_{up,t-k} + \sum_{k=1}^{K} d_{k,up} R_{B,t-k} \cdot D_{up,t-k} + \sum_{k=1}^{K} c_{k,down} R_{s,t-k} \cdot D_{down,t-k} + \sum_{k=1}^{K} d_{k,down} R_{B,t-k} \cdot D_{down,t-k} + v_t \quad (6)$$

In Equations (5) and (6), $D_{up,t\text{-}k}$ and $D_{down,t\text{-}k}$ are dummy variables, which correspondingly reflect the up and down markets conditions at period t-k. $D_{up,t\text{-}k}$ equals one if the market condition becomes up and zero otherwise. In a similar way, $D_{down,t\text{-}k}$ equals one if the market state is down and zero otherwise. The reason that two dummy variables are set is to achieve the VAR investigations independently of the up and down conditions. For example, we examine whether big firms react faster than smaller firms to acquire common information in the down market state by employing a cross-equation test of null hypothesis: $\sum_{k=1}^{K} b_{K,down} = \sum_{k=1}^{K} c_{K,down}$. On the other hand, in an up market condition, we examine whether big firms react faster than smaller firms to acquire common information by using a cross-equation test of null hypothesis: $\sum_{k=1}^{K} b_{K,up} = \sum_{k=1}^{K} c_{K,up}$.

In Equation (5), $a_{k,\,up}$ and $b_{k,\,up}$ are the coefficients of the lagged returns of R_S and R_B in a up market state, respectively. $a_{k,\,down}$ and $b_{k,\,down}$ are the coefficients of the lagged returns of R_S and R_B in down market state correspondingly. Similarly, in Equation (6), $c_{k,\,up}$ and $d_{k,\,up}$ are, respectively, the coefficients of the lagged returns of R_S and R_B in up market state, while $c_{k,\,down}$ and $d_{k,\,down}$ are the coefficients of the lagged returns of R_S and R_B in a down market state.

With regards to the smaller firms' current returns, $\sum_{k=1}^{K} b_{K,up}$ and $\sum_{k=1}^{K} b_{K,down}$ reflect the impact of the big firms' lagged returns in an up market state and the impact of the big firms' lagged returns in a down market state. Greater coefficients show more striking cross-autocorrelations between the big firms' lagged returns and the smaller firms' current returns, which suggest that the more significant lead-lag relation between big and small firms. As the lead-lag relation reflects slow diffusion of information from big to small firms, the more significant lead-lag effect suggests a slower diffusion of information. (Most studies argue that slow diffusion of common information is a primary cause of the lead-lag effect. Thus, the stronger lead-lag effect suggests slower diffusion of information [1,4,8–10].) Therefore, in order to estimate the speed of intra-industry information diffusion in different market conditions, we compare $\sum_{k=1}^{K} b_{K,down}$ and $\sum_{k=1}^{K} b_{K,up}$. If $\sum_{k=1}^{K} b_{K,down} > \sum_{k=1}^{K} c_{K,up}$, intra-industry information diffusion is slower in a down market state, and vice versa.

4.1. Shorter Horizon of Market Conditions

Based on the seven sample industries, we first employ the previous four-week market returns to be the shorter horizon of market conditions. The time-series empirical results of the seven industries are stated in Table 4:

In Panel A of Table 4, in regards to the small firms' current returns, "Big-up" is the sum of coefficients of the lagged big firms' returns in an up market state, reflecting the impact of the big firms' lagged returns in an up market state. On the contrary, "Big-down" denotes the sum of coefficients of lagged big firms' returns in a down market state, revealing the impact of the big firms' lagged returns. It is found that the "Big-down" is greater than the "Big-up" in all industries (except the electronic equipment industry and the industrial engineering industry that are not significant). It shows that the impact of the big firms' lagged returns in a down market state is greater than the impact of the big firms' lagged returns in the up market state. Furthermore, the cross-equation test is more significant in the down market in four of the industries. These results display the more significant lead-lag effect in down market state, which suggest that slower information diffusion appears in the down market state than the up market state. The results also suggest that there are more obstacles in the process of intra-industry information diffusion when market condition becomes a down market state. Furthermore, to process an entire investigation of intra-industry, a conditional panel VAR is employed by including all firms. Panel B of Table 4 displays the conditional panel VAR in a shorter horizon.

Table 4. Conditional Vector Auto-regression (VAR) in Shorter Horizon of Market condition.

Industry		Conditional Vector Auto-Regression				
		Small-up	**Big-up**	**Small-down**	**Big-down**	**Cross-Equation Tests**
Panel A: The time-series Conditional VAR						
Automobiles parts	R_S	−0.111	0.582 ***	−0.614 ***	0.654 ***	Up:
		(0.315)	(7.218)	(6.164)	(6.273)	0.652
	R_B	−0.410 **	0.735 ***	−0.666 ***	0.629 ***	Down:
		(5.473)	(13.527)	(8.850)	(7.048)	27.446 ***
Construction and materials	R_S	−0.376	0.748 ***	−0.728**	0.750 ***	Up:
		(2.254)	(6.986)	(6.175)	(7.013)	15.393 ***
	R_B	−0.364	0.628 **	−0.693 **	0.68 5**	Down:
		(2.474)	(5.710)	(6.548)	(5.822)	22.096 ***
Electronic equipment	R_S	0.065	0.189	−0.286	0.305	Up:
		(0.059)	(0.386)	(0.651)	(0.682)	1.126
	R_B	−0.134	0.240	−0.120	0.043	Down:
		(0.289)	(0.709)	(0.131)	(0.015)	1.324
Food producers	R_S	−0.413	0.616 **	−0.610 **	0.774 ***	Up:
		(2.455)	(4.233)	(5.165)	(6.821)	11.302 ***
	R_B	−0.391	0.498 *	−0.615 **	0.734 ***	Down:
		(2.570)	(3.226)	(6.144)	(7.168)	21.958 ***
Industrial engineering	R_S	0.052	0.236	−0.264	0.269	Up:
		(0.069)	(1.066)	(0.876)	(1.141)	2.415
	R_B	−0.119	0.379 *	−0.241	0.221	Down:
		(0.397)	(2.983)	(0.792)	(0.690)	3.766 *
Industrial metals and mining	R_S	0.148	0.214 *	−0.257	0.318 *	Up:
		(0.545)	(2.810)	(1.293)	(2.773)	1.668
	R_B	−0.061	0.309 *	−0.196 *	0.189 *	Down:
		(−0.061)	(2.842)	(3.487)	(2.922)	4.374 **
Pharmaceuticals and biotechnology	R_S	0.405 *	0.198 *	−0.404	0.521 *	Up:
		(3.574)	(2.746)	(2.380)	(3.006)	1.661
	R_B	0.147	0.072	−0.499 **	0.500 **	Down:
		(0.661)	(0.102)	(5.108)	(3.886)	11.532 ***
Panel B: The Panel Conditional VAR						
All sample industries	$R_{S,i}$	0.028	0.296 ***	−0.389 ***	0.420 ***	Up:
		(0.12)	(10.03)	(14.61)	(15.35)	23.70 ***
	$R_{B,i}$	−0.159 **	0.397 ***	−0.359 ***	0.328 ***	Down:
		(4.33)	(20.66)	(14.21)	(10.69)	52.74 ***

Notes: R_S is the equal-weighted weekly return on the smallest 30% portfolio, while R_B presents the equal-weighted weekly return on the largest 30% portfolio. $R_{S,i}(t)$ and $R_{B,i}(t)$ are the equal-weighted weekly return on the portfolio of the smallest and the largest 30% firms at period t in industry i, correspondingly. Small-up indicates the sum of coefficients of lagged small firms' returns in up market. Small-down show the sum of coefficients of lagged small firms' returns in down market. Small-up indicates the sum of coefficients of lagged small firms' returns in up market. Small-down show the sum of coefficients of lagged small firms' returns in down market. On the other hand, Big-up indicates the sum of coefficients of lagged big firms' returns in up market, while Big-down denotes the sum of coefficients of lagged big firms' returns in down market. F-statistics are reported in parentheses. Furthermore, in cross-equation tests, Up is the F-statistic for the null hypothesis in up market i.e., $\sum_{k=1}^{4} b_{K,up} = \sum_{k=1}^{4} c_{K,up}$. Down is F-statistic for the null hypothesis in down market i.e., $\sum_{k=1}^{4} b_{K,down} = \sum_{k=1}^{4} c_{K,down}$. Finally, ***, **, and * denote significance at the 1, 5, and 10% levels, respectively. Both AIC and HQIC information criterions support the four-lag to be adaptive order criteria. Thus, four-lag is used in the VAR model. (The result is similar with the view of Hou [4]. He claims that the lag order should be one or four because it is reasonable to assume that small firms will react to information within a month's time.)

Regarding the small firms' current returns, "Big-up" is 0.296 and "Big-down" equals 0.420. Both are significant at the 1% level. It shows that the impact of the big firms' lagged returns in the down market state is greater than the impact of the big firms' lagged returns in the up market state. These results display the more significant lead-lag effect in the down market state, which suggest that slower information diffusion appears in down market state. Therefore, the results of the conditional panel VAR also support that the intra-industry information diffusion from big firms to small firms becomes slower in down market state than the up market state. (The results of value weighted portfolios are consistent. The results are available upon request.)

The results are consistent with Hameed and Kusnadi's study [3], which claims that the speed of information diffusion becomes faster in the up market condition rather than the down market condition. On the other hand, Hong et al. [38], Doukas and McKnight [39], and Yalçın [40] argue that bad news diffuses slower in the market. When the market is turning downward, increasingly bad information is full of the market. However, firms react slower to bad news, especially the smaller ones. Negative information diffuses more slowly from big firms to small firms in a down market. Therefore, the gradual intra-industry information diffusion is more significant when the market goes down. Additionally, from another aspect, as the market continually declines, pessimistic sentiment is full of the market. Thus, investors ultimately lose investment confidence and they take less notice of the stocks. Da et al. [41,42] discuss that less investors' attention generates slower information diffusion. Consequently, slower information diffusion appears more easily in the down market.

4.2. Longer Horizon of Market Conditions

As a robustness check, a longer horizon of market condition (previous 26-week market return) is also employed to explore the impact of market conditions on intra-industry information diffusion. The empirical results of seven industries are shown in Table 5:

Table 5. Conditional VAR in Longer Horizon of Market condition.

Industry		Conditional Vector Auto-Regression				
		Small-up	Big-up	Small-down	Big-down	Cross-Equation Tests
Panel A: The time-series Conditional VAR						
Automobiles parts	R_S	−0.043	0.386 *	−0.637 ***	0.815 ***	Up:
		(0.050)	(3.400)	(7.482)	(11.269)	11.996 ***
	R_B	−0.339 *	0.539 ***	−0.698 ***	0.803 ***	Down:
		(3.526)	(7.498)	(10.152)	(12.342)	38.835 ***
Construction and materials	R_S	−0.246	0.521 *	−0.770 ***	0.919 ***	Up:
		(0.943)	(3.667)	(7.426)	(8.935)	7.906 ***
	R_B	−0.244	0.430 *	−0.753 ***	0.846 ***	Down:
		(1.080)	(2.902)	(8.281)	(8.826)	29.572 ***
Electronic equipment	R_S	0.068	0.069	−0.276	0.398	Up:
		(0.067)	(0.056)	(0.577)	(1.071)	0.320
	R_B	−0.096	0.109	−0.138	0.140	Down:
		(0.156)	(0.159)	(0.165)	(0.150)	1.943
Food producers	R_S	−0.246	0.521 *	−0.767 ***	0.919 ***	Up:
		(0.943)	(3.667)	(7.426)	(8.935)	7.907 ***
	R_B	−0.244	0.430 *	−0.753 ***	0.846 ***	Down:
		(1.079)	(2.902)	(8.281)	(8.826)	29.901 ***
Industrial engineering	R_S	0.225	0.018	−0.581**	0.701**	Up:
		(1.368)	(0.008)	(4.203)	(5.839)	0.110
	R_B	0.049	0.093	−0.529 *	0.613 **	Down:
		(0.069)	(0.229)	(3.739)	(4.798)	12.902 ***
Industrial metals and mining	R_S	0.264	0.029 *	−0.341 *	0.490 **	Up:
		(1.643)	(3.020)	(2.515)	(4.300)	0.272
	R_B	−0.078	0.120	−0.299	0.358 *	Down:
		(0.152)	(0.360)	(2.003)	(2.798)	11.146 ***
Pharmaceuticals and biotechnology	R_S	0.400 *	0.217**	−0.318 *	0.486 **	Up:
		(3.565)	(4.689)	(1.978)	(4.393)	1.074
	R_B	0.054	0.136	−0.297	0.362 *	Down:
		(0.090)	(0.380)	(1.928)	(2.868)	7.246 ***
Panel B: The Panel Conditional VAR						
All sample industries	$R_{S,i}(t)$	0.143	0.097	−0.493 ***	0.626 ***	Up:
		(0.145)	(1.20)	(24.63)	(34.62)	2.52
	$R_{B,i}(t)$	−0.044 **	0.201 ***	−0.465 ***	0.528 ***	Down:
		(4.33)	(20.66)	(25.00)	(28.07)	105.11 ***

Notes: The settings of coefficients are same to Table 4.

Consistent with the analysis of the four-week horizon of market condition, the time-series empirical results show that market conditions affect intra-industry information diffusion under the investigation of a longer horizon of market condition. The results also suggest that the gradual intra-industry information diffusion is more significant in the down market state than the up market state.

As stated in Panel B, in regards to the small firms' current returns, "Big-down" is much bigger and significant than the "Big-up". It shows that the impact of the big firms' lagged returns in a down market state is greater than the impact of the big firms' lagged returns in an up market state. Moreover, we find that the cross-equation test (F = 105.11) is significant only in a down market state. These results display the more significant lead-lag effect in down market state as compared to the up market state, which suggest that slower information diffusion appears in down market state. Therefore, the results of the conditional panel VAR also suggest that information diffusion from big firms to small firms becomes slower in the down market condition than the up market condition under the analysis of a longer horizon of market condition.

When compared to Table 4, the results of a longer horizon of market condition are more significant than the results of a shorter horizon of market condition. These results also suggest that when the market turned downwards for a longer period, the speed of intra-industry information diffusion develops more slowly. As the longer bearish market exists, investors become gloomier and their investment sentiment becomes lower. Hence, many investors might lose investment interest on stocks. Consequently, when the market falls off for a longer period, less investors' attention is brought into the market. Thus, when compared to a shorter horizon down market condition, information diffuses more slowly in a longer horizon down market condition.

5. Policy Change and Intra-Industry Information Diffusion

5.1. Examining the Impact of Policy Changes

There are two most important policy changes in China: the split-share structure reform in 2005 and lifting the short-sale constraints in 2010. These significant times in policy changes have generated two break points. The full study period is divided into three sub-periods: January 2002–February 2005, March 2005–January 2010, and February 2010–December 2013. The first sub-period mainly shows the situation of China's stock market before the split-share structure reform and the lifting of the short-sale constraints. What happens in China's stock market after the split-share structure reform is displayed in the second sub-period. Meanwhile, the second sub-period also shows the situation of China's stock market with the short-sale constraints. After lifting the short-sale constraints and the split-share structure reform, the situation is presented in the last sub-period.

Therefore, in order to examine the impact of policy changes from 2002 to 2013 on intra-industry information diffusion over time, the VAR procedure is continuously employed to estimate the lead-lag effect between the big and small firms. Three dummy variables, i.e., D_{p1}, D_{p2}, and D_{p3}, are added into the original VAR model. Hence, the new conditional VAR model is stated in the underlying equations:

$$R_{S,t} = a_0 + \sum_{k=1}^{K} a_{k,p1} R_{s,t-k} \cdot D_{p1,t-k} + \sum_{k=1}^{K} b_{k,p1} R_{B,t-k} \cdot D_{p1,t-k} + \sum_{k=1}^{K} a_{k,p2} R_{s,t-k} \cdot D_{p2,t-k} + \sum_{k=1}^{K} b_{k,p2} R_{B,t-k} \cdot D_{p2,t-k} + \sum_{k=1}^{K} a_{k,p3} R_{s,t-k} \cdot D_{p3,t-k} + \sum_{k=1}^{K} b_{k,p3} R_{B,t-k} \cdot D_{p3,t-k} + u_t \quad (7)$$

$$R_{B,t} = a_0 + \sum_{k=1}^{K} c_{k,p1} R_{s,t-k} \cdot D_{p1,t-k} + \sum_{k=1}^{K} d_{k,p1} R_{B,t-k} \cdot D_{p1,t-k} + \sum_{k=1}^{K} c_{k,p2} R_{s,t-k} \cdot D_{p2,t-k} + \sum_{k=1}^{K} d_{k,p2} R_{B,t-k} \cdot D_{p2,t-k} + \sum_{k=1}^{K} c_{k,p3} R_{s,t-k} \cdot D_{p3,t-k} + \sum_{k=1}^{K} d_{k,p3} R_{B,t-k} \cdot D_{p3,t-k} + v_t \quad (8)$$

In Equations (7) and (8), $D_{p1,\ t\text{-}k}$, $D_{p2,\ t\text{-}k}$, and $D_{p3,\ t\text{-}k}$ are dummy variables, which respectively reflect the three sub-periods at period t-k. $D_{p1,\ t\text{-}k}$ equals one if the market is in the first sub-period (January 2002–February 2005) and zero otherwise. In a similar way, $D_{p2,\ t\text{-}k}$ equals one if the market is in the second sub-period (March 2005–January 2010) and is zero otherwise. $D_{p3,\ t\text{-}k}$ equals one if the market is in the third sub-period (February 2010–December 2013) and zero, or else. The purpose for setting the three dummy variables is to identify the VAR analysis separately for the different sub-periods. For example, the study examines whether big firms react faster than the smaller firms to common information in the first sub-period by employing a cross-equation test for null hypothesis: $\sum_{k=1}^{k} \mathrm{b}_{K,\mathrm{p}1} = \sum_{k=1}^{k} \mathrm{c}_{K,\mathrm{p}1}$. Similarly, a cross-equation test for the null hypothesis is used in the second (third) sub-period: $\sum_{k=1}^{k} \mathrm{b}_{K,\mathrm{p}2} = \sum_{k=1}^{k} \mathrm{c}_{K,\mathrm{p}2}$. ($\sum_{k=1}^{k} \mathrm{b}_{K,\mathrm{p}3} = \sum_{k=1}^{k} \mathrm{c}_{K,\mathrm{p}3}$.).

In Equation (7), $a_{\mathrm{k},p1}$ and $\mathrm{b}_{\mathrm{k},p1}$ ($a_{\mathrm{k},p2}$ and $\mathrm{b}_{\mathrm{k},p2}$; $a_{\mathrm{k},p3}$ and $\mathrm{b}_{\mathrm{k},p3}$) are the coefficients of the lagged returns of R_S and R_B, in the first (second; third) sub-period, correspondingly. Similarly, in Equation (8), $\mathrm{c}_{\mathrm{k},p1}$ and $\mathrm{d}_{\mathrm{k},p1}$ ($\mathrm{c}_{\mathrm{k},p2}$ and $\mathrm{d}_{\mathrm{k},p2}$; $\mathrm{c}_{\mathrm{k},p3}$ and $\mathrm{d}_{\mathrm{k},p3}$) are, respectively, the coefficients of the lagged returns of R_S and R_B in the first (second; third) sub-period.

In this conditional VAR setting, significances of coefficients are similar with the original VAR model. With regards to the smaller firms' current returns, $\sum_{k=1}^{K} b_{K,p1}$, $\sum_{k=1}^{K} b_{K,p2}$, and $\sum_{k=1}^{K} b_{K,p3}$ correspondingly reflect the impact of the big firms' lagged returns in the first, second, and third sub-periods. A greater coefficient shows more impact of the big firms' lagged returns on the small firms' current returns, which suggest a more prominent lead-lag relation between the bigger and smaller firms. Thus, a greater coefficient reflects slower diffusion of information from big firms to the smaller ones in this sub-period. By comparing $\sum_{k=1}^{K} b_{K,p1}$, $\sum_{k=1}^{K} b_{K,p2}$, and $\sum_{k=1}^{K} b_{K,p3}$, an estimation of the impact of policy changes on intra-industry information diffusion in different sub-periods is made.

Based on Panel A of Table 6, there is no strong statistical evidence to discover the relatively consistent intra-industry information diffusion in the second and third sub-periods. Most coefficients are insignificant or marginal significant in either one sub-period only (except the automobile parts industry and the construction and materials industry). Additionally, the cross-equation tests are also unable to show consistent results among the industries (except the automobile parts industry and the construction and materials industry). Due to these inconsistent results among the industries, we further employ panel data analysis by including all firms. Panel B of Table 6 displays the results of the panel data.

Based on Panel B, among the three coefficients in the small firms' current returns, "Big-P_3" is the biggest and "Big-P_2" is in the middle, whereas "Big-P_1" is the smallest. These results suggest that the intra-industry lead-lag effect becomes stronger over time. Therefore, intra-industry information diffusion from big firms to smaller firms becomes slower from the first sub-period to the third sub-period. The policy changes impede intra-industry information diffusion. More delay is brought into intra-industry information diffusion along with the policy changes.

Next, as for the robustness test, we separately employ the conditional panel VAR to analyze intra-industry information diffusion in each sub-period. The empirical results are described in Table 7.

With regards to the smaller firms' current returns, the sum of coefficients of big firms' lagged returns is correspondingly 0.069, 0.277, and 0.438 in the three sub-periods, respectively. They increase over time and are only statistically significant in the latter two sub-periods. Therefore, the impact of the big firms' lagged returns on the smaller firms' current returns becomes bigger over time. The results suggest that the lead-lag effect between the big firms and smaller firms becomes stronger over time. Thus, intra-industry information diffusion from big firms to small firms becomes slower over time. As a result, the policy changes influence the intra-industry information diffusion, which suggests that more delay is brought into the process of intra-industry information diffusion over time.

Table 6. Conditional VAR for Policy Changes.

Industry		Three Sub-Pperiods						Cross-Equation Tests		
		Small-P_1	**Big-P_1**	**Small-P_2**	**Big-P_2**	**Small-P_3**	**Big-P_3**	**Test-P_1**	**Test-P_2**	**Test-P_3**
Panel A: The time-series Conditional VAR										
Automobiles parts	R_S	−0.468	0.373	−0.241	0.523 **	−0.377	0.636 *			
		(1.664)	(0.767)	(1.598)	(6.565)	(1.345)	(3.582)	1.710	29.071 ***	10.754 ***
	R_B	−0.184	0.250	−0.578 ***	0.755 ***	−0.466	0.519 *			
		(0.293)	(0.390)	(10.473)	(15.450)	(2.344)	(2.712)			
Construction and materials	R_S	−0.693	0.575	−0.345	0.563 **	−0.644 *	0.830 **			
		(1.653)	(0.663)	(1.771)	(4.126)	(2.953)	(5.142)	2.035	12.580 ***	16.689 ***
	R_B	−0.433	0.295	−0.420 *	0.592**	−0.665 *	0.673 **			
		(0.753)	(0.204)	(3.078)	(5.335)	(3.673)	(3.951)			
Electronic equipment	R_S	0.425	0.717	−0.153	0.371	−0.368	0.477			
		(0.817)	(2.190)	(0.344)	(1.723)	(0.373)	(0.544)	4.191 **	4.920 **	0.907
	R_B	0.275	−0.662	−0.256	0.336	−0.139	0.152			
		(0.392)	(2.131)	(1.111)	(1.616)	(0.060)	(0.063)			
Food roducers	R_S	−0.480	0.215	0.030	0.148	−0.004	0.027			
		(0.797)	(0.180)	(0.011)	(0.237)	(0.068)	(0.003)	2.535	0.051	0.007
	R_B	−0.592	0.383	0.079	0.030	0.066	−0.017			
		(1.364)	(0.642)	(0.090)	(0.011)	(0.026)	(0.001)			
Industrial engineering	R_S	−0.489	0.261	0.110	0.062	−0.502	0.690 *			
		(0.820)	(0.187)	(0.355)	(0.108)	(1.594)	(2.897)	2.028	0.193	8.073 *
	R_B	−0.597	0.366	−0.021	0.175	−0.462	0.507			
		(1.334)	(0.403)	(0.014)	(0.927)	(1.467)	(1.699)			
Industrial metals and mining	R_S	−0.397	0.146	0.144	0.082	−0.358	0.580 *			
		(1.682)	(0.203)	(0.541)	(0.159)	(1.171)	(2.880)	2.199	0.066	8.731 ***
	R_B	−0.335	0.161	0.029	0.120	−0.430	0.481			
		(1.258)	(0.258)	(0.023)	(0.354)	(1.172)	(2.077)			
Pharmaceuticals and biotechnology	R_S	−0.500	0.262	−0.023	0.307	0.404	0.406			
		(0.708)	(0.141)	(0.014)	(1.605)	(1.526)	(1.188)	0.911	5.175**	2.577
	R_B	−0.404	0.252	−0.244	0.455 **	0.192	0.245			
		(0.640)	(0.181)	(2.158)	(4.905)	(0.478)	(0.600)			
Panel B: The Panel Conditional VAR										
All sample industries	$R_{S,i}(t)$	−0.353**	0.112	−0.048	0.267 ***	−0.262*	0.421 ***			
		(5.07)	(0.41)	(0.38)	(9.64)	(3.62)	(8.47)	4.84**	30.25 ***	35.05 ***
	$R_{B,i}(t)$	−0.272*	0.077	−0.206 ***	0.352 ***	−0.303**	0.343**			
		(3.43)	(0.23)	(7.72)	(19.12)	(5.52)	(6.45)			

Notes: R_S and R_B are the equal-weighted weekly return on the smallest and the largest 30% firms, correspondingly. $R_{S,i}(t)$ and $R_{B,i}(t)$ are the equal-weighted weekly return on the portfolio of the smallest and the largest 30% firms at period t in industry i, correspondingly. Small-P_1 and Big-P_1 respectively indicate the sum of coefficients of lagged small firms' returns and the sum of coefficients of lagged big firms' returns in the first sub-period. Similarly, Small-P_2 and Big-P_2, respectively, refer to the sum of coefficients of lagged small firms' returns and lagged big firms' returns in the second sub-period. Small-P_3 and Big-P_3 respectively refer to the sum of coefficients of lagged small firms' returns and lagged big firms' returns in the third sub-period. F-statistics are reported in parentheses. Test-P_1 is F-statistics for cross-equation tests for the null hypothesis in the first sub-period i.e., $\sum_{k=1}^{4} bk,_{P1} = \sum_{k=1}^{4} ck,_{P1}$., Test-$P_2$ and Test-P_3 are also corresponding F-statistics in the second sub-period and the third sub-period. Finally, ***, **, and * denote significance at the 1, 5, and 10 % levels, respectively. Both AIC and HQIC information criterions support the four-lag to be adaptive order criteria. Thus, four-lag is used in the VAR model.

Additionally, by observing the "Big-P_1", "Big-P_2", and "Big-P_3" in Table 6 and the sum of coefficients of big firms' lagged returns in Table 7, it is discovered that the sum of coefficients of big firms' lagged return decreasingly increase over time, i.e., the growth rate of the sum of coefficients decreases from sub-period 1 to sub-period 2 and from sub-period 2 to sub-period 3. It is found that the first policy change, i.e., the split-share structure reform, has more impact on intra-industry information diffusion than the lifting of short-sale constraints. The empirical results show that the split-share structure reform actually impedes the process of intra-industry information diffusion. However, most people think that the reforms help to improve market efficiency. Do the reforms improve market efficiency? As the most powerful policy reform of China stock market in recent years, the potential impacts of the split share structure reform have been discussed by a few empirical researches. However, effectiveness of the split share structure reform is still in dispute. For example, Chen et al. [13] argue that the split share structure reform improves the liquidity of the market and increases the market efficiency. Yet, Beltratti et al. [25] discover this reform had no impact on the ownership structure of firms in their research. They argue that only some small stocks and historically neglected stocks are partially beneficial from this reform. Additionally, Carpenter et al. [27] suggest that the split share structure reform has little direct immediate impact on the structure of the China stock market in the short term.

Table 7. Separate Panel VAR in Three Sub-periods.

	$\sum_{K=1}^{4} R_{S,i}$(t-k)	$\sum_{K=1}^{4} R_{B,i}$(t-k)	Cross-equation tests $\sum_{k=1}^{4} b_k = \sum_{k=1}^{4} c_k$
Sub-period1: Jan 2002–Feb 2005			
$R_{S,i}$(t)	−0.454 ***	0.069	11.86 ***
	(16.99)	(0.33)	
$R_{B,i}$(t)	−0.347 ***	0.058	
	(12.46)	(0.29)	
Sub-period2: Mar 2005–Jan 2010			
$R_{S,i}$(t)	−0.070	0.277 **	20.75 ***
	(0.47)	(6.27)	
$R_{B,i}$(t)	−0.227 **	0.359 ***	
	(5.71)	(12.16)	
Sub-period3: Feb 2010–Dec 2013			
$R_{S,i}$(t)	−0.282 ***	0.438 ***	43.02 ***
	(6.84)	(15.01)	
$R_{B,i}$(t)	−0.304 ***	0.340 ***	
	(8.38)	(9.55)	

Notes: $R_{S,i}$(t) and $R_{B,i}$(t) are the equal-weighted weekly return on the smallest and the largest 30% firms at period t in industry i, correspondingly. $R_{S,i}$(t-k) and $R_{B,i}$(t-k), respectively, are the equal-weighted weekly return on the smallest and the largest 30% firms at period t-k in industry i. Cross-equation test denotes F-statistic for the cross-equation null hypothesis: $\sum_{k=1}^{4}$ bk = $\sum_{k=1}^{4}$ ck. Finally, ***, **, and * denote significance at the 1, 5, and 10 % levels, respectively. Both AIC and HQIC information criterions support the four-lag to be adaptive order criteria.

5.2. Additional Tests on the Impact of Policy Changes

5.2.1. The Time-series Change of Lead-lag Effects among Three Sub-periods

In the previous analysis, the impact of policy changes on intra-industry information diffusion is examined by considering the impact of lagged big firms' returns on the current smaller firms' returns and vice versa. Contrary to the previous section and following Mori [17], the effect of small firms leading to big firms is subsequently excluded. Only the lead-lag effect from big firms to small firms is exhibited. The lead-lag effect is estimated in a one-lag panel VAR that is based on the weekly returns of the same equal-weighted size portfolios with a quarterly window. More specifically, the one-lag panel VAR is stated in the following equations:

$$R_{S,i(t)} = a_{i,0} + a_1 R_{S,i(t-1)} + b_1 R_{B,i(t-1)} + u_{i,t} \tag{9}$$

$$R_{B,i(t)} = c_{i,0} + c_1 R_{S,i(t-1)} + d_1 R_{B,i(t-1)} + v_{i,t} \tag{10}$$

In Equations (9) and (10), $R_{S,i}$(t) and $R_{S,i}$(t-1) are the weekly returns of the smallest 30% portfolio at period t and period t-1, respectively, in industry i, while $R_{B,i}$(t) and $R_{B,i}$(t-1) present the weekly returns of the largest 30% portfolio at period t and period t-1 in industry i.

According to Mori [17], the time-series lead-lag effect could be evaluated by acquiring the difference between b_1 in Equation (9) and c_1 in Equation (10), which examines the size of the lead-lag effect from big firms to smaller firms. Although Mori [17] only investigates the Real Estate Investment Trust market in the U.S., this method is a better reference for our underlying analysis. Furthermore, b_1 actually implies the effect that big firms lead small firms, while c_1 suggests the effect that small firms lead big firms. Therefore, (b_1–c_1) evaluates the lead-lag effect from big firms to small firms, while control for the reverse lead-lag effect from small firms to big firms. If big firms actually could lead small firms, then b_1 should be greater than c_1 and (b_1–c_1) should be greater than zero. It presents a distinct lead-lag effect between big and small firms, which reflects that the delayed degree of information diffusion is stronger from big firms to smaller firms. Additionally, if (b_1–c_1) is less than zero, it implies that, instead of the lead-lag effect from big firms to small firms, the reverse lead-lag effect from small firms to big firms appears.

Table 8 shows the mean and standard deviation of (b_1–c_1) in each three sub-periods. First, the mean becomes bigger over time. It suggests that the lead-lag effects develop stronger from the first sub-period to the last sub-period. Second, the F-statistic for mean difference among three sub-periods is significant at the 1% level. Thus, intra-industry information diffusion is also dissimilar in different sub-periods. Based on the above two viewpoints, the delay of intra-industry information diffusion from big stocks to small stocks becomes greater over time, which imply that policy changes impede intra-industry information diffusion. These results support our results in the previous section.

Table 8. Mean compare and variance compare among Three Sub-periods.

Sub-Period	Mean	Std	Comparison Sub-Period	Mean Difference
Sub-period 1	−0.313	1.669	Sub-period 2	−0.711**
			Sub-period 3	−1.009**
Sub-period 2	0.398	1.562	Sub-period 1	0.711**
			Sub-period 3	−0.298
Sub-period 3	0.696	1.517	Sub-period 1	1.009**
			Sub-period 2	0.298
F-test	12.459 ***	2.658*		

Notes: Mean denotes mean of (b_1–c_1) in the sub-period. Std refers to standard deviation of (b_1–c_1) in the sub-period. F-test refers to F-statistics for mean compare and variance compare among three sub-periods. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively. Mean Difference denotes the difference of mean between sub-periods.

On the other hand, the standard deviations of (b_1–c_1) show a downtrend over time. Moreover, the F-statistic for standard deviation difference among the three sub-periods is significant at the 10% level, which suggests that the difference of standard deviation exists among the three sub-periods. The results show that the volatility of lead-lag effects decrease over time, which suggests that the fluctuation amplitude of information diffusion reduces over time. Consequently, these results support the information volatility of China's stock market declines, along with its policy changes. With the policy changes, the information environment and transparency of market improve over time. Informational efficiency and transparency are brought into the Chinese stock market.

Table 8 also exhibits multiple comparisons of the mean among the three sub-periods. However, the difference of mean between sub-period 1 and sub-period 2, as well as the difference of mean between sub-period 1 and sub-period 3 are significant. The demarcation of the sub-period 1 depends on the first policy change, i.e., the split-share structure reform. Consequently, the impact of the split-share structure reform on the information diffusion has been relatively substantial. On the other hand, the difference of mean between sub-period 3 and sub-period 2 is insignificant. The demarcation of sub-period 3 depends on the second policy change, i.e., lifting of the short-sale constraints. Therefore, lifting short-sale constraints has less impact on information diffusion. As a result, the impact of the split-share structure reform in 2005 is more significant to intra-industry information diffusion in China, which generates more friction of intra-industry information diffusion.

5.2.2. Potential Reasons on the Lead-lag Changes

With the intention of investigating the potential reasons of increasing delay of intra-industry information diffusion over time, further analysis is stated in Table 9:

Table 9. Comparison of Market Situations among Three Sub-periods.

Variables	Mean	Std	Max	Min	F-Test	
Sub-period 1: Jan 2002–Feb 2005					Mean	Variance
Market-return	−0.029	0.106	0.152	−0.218	1.529	12.206 ***
Market-capitalization	41032	4867	50417	31590	41.792 ***	72.619 ***
Market-trading volume	414	179	682	137	31.087 ***	34.727 ***
Proportion-institutional	0.0056	8.64E-05	0.0057	0.0055	48.305 ***	62.510 ***
Proportion-individual	0.9943	8.64E-05	0.9945	0.9943	48.305 ***	62.510 ***
Sub-period 2: Mar 2005–Jan 2010						
Market-return	0.056	0.221	0.425	-0.416		
Market-capitalization	151824	87563	327140	32430		
Market-trading volume	2552	1334	4454	506		
Proportion-institutional	0.0052	0.0059	0.0059	0.0046		
Proportion-individual	0.9947	0.00042	0.9954	0.9941		
Sub-period 3: Feb 2010–Dec 2013						
Market-return	−0.026	0.101	0.101	−0.260		
Market-capitalization	233433	22013	277662	195138		
Market- trading volume	3226	956	5015	1961		
Proportion- institutional	0.0046	4.58E-05	0.0047	0.0045		
Proportion-individual	0.9953	4.58E-05	0.9954	0.9953		

Notes: Degree-lead lag is (b_1–c_1). F-test refers to F-statistics for mean compare and variance compare among three sub-periods. Finally, ***, **, and * refer to significance at the 1, 5, and 10% levels, respectively.

Table 9 describes the comparison of the different market situations among three sub-periods in China's stock market. As shown, market capitalization and market trading volume grow over time, which suggest the booming development of China's stock market. However, as opposed to the general uptrend of the proportions of individual investors, the proportion of institutional investors remarkably declines, especially after the split-share structure reform in 2005. This result is not consistent with many developed markets. An advanced market eventually needs more institutional investors. However, with the expansion of China's stock market, the proportion of institutional investors is not rising, while the proportion of individual investors is on the rise.

Due to the lack of information processing capacity and channel, most Chinese individual investors tend to follow institutional investors who possess superiority in information acquisition [43,44]. Hence, information generally diffuses from institutional investors to individual investors in China's stock market [45,46]. Reduced institutional investors might make the information diffusion more gradual between institutional investors and individual investors. As a result, the increasing proportion of individual investors and the decreasing proportion of institutional investors could potentially cause the delay of intra-industry information diffusion over time in China.

6. Conclusions

This paper investigates the impact of market conditions and policy changes on intra-industry information diffusion in China. Different with previous studies [4–6,18], the study focuses on intra-industry to investigate the process of information diffusion with view of both market conditions and policy changes. Moreover, according to specific conditions in China, different from previous studies [7,21], as far as we know, this paper is the first paper studying the impact of market conditions and policy changes on intra-industry information diffusion in China.

The main findings are: first, the market conditions significantly affect the process of intra-industry information diffusion. The speed of intra-industry information diffusion in the down market condition is slower than in the up market condition. Conversely, when the market is turning upward, the speed of intra-industry information diffusion develops faster. Second, the impact of a longer horizon of market condition is more significant than the shorter horizon. In other words, when the market turns downward for a longer period, the speed of intra-industry information diffusion develops more slowly. These findings are consistent with the gradual-information diffusion theory of Hong et al. [38]. They suggest that, when the market falls off, the market is full of negative information and negative information diffuses more slowly across the market. Market frictions are responsible for the gradual diffusion of information. Moreover, the impact of market frictions is usually more prominent when bad news arrives (for example, the short sale constraint will delay the incorporation of negative information into stock prices [28]).

This finding provides some trading strategies for investors. When good common information comes to some big firms, based on the principle of gradual information diffusion, investors usually choose small firms from the whole market. However, it is suggested that investors should choose high quality small firms from the same industry, rather than the whole market. Investors should take long positions in these stocks as early as possible and then wait for potential abnormal profit. When the market falls off, investors should slow these investments. Alternatively, investors might accelerate investment behaviors as the market turns upward.

Third, the policy change also has an effect on intra-industry information diffusion. Especially, we find that the split-share structure reform actually impedes the process of intra-industry information diffusion. These findings are consistent with previous theories, such as Merton [14], Lin and Swanson [15], and Mori [17], which mean some external institutional restrictions, such as policy changes, could significantly affect the process of information intra-industry information diffusion. The intra-industry information diffusion from big firms to small firms becomes slower along with policy changes. These results show that due to the policy changes in China, more delay is brought into the process of intra-industry information diffusion over time. Therefore, policy changes impede intra-industry information diffusion.

Fourth, there is a continuously decreasing information volatility of intra-industry information diffusion in China's stock market. Along with the policy changes in China's stock market, the information environment and transparency of market are improved over time. Fifth, the impact of the split-share structure reform in 2005 is more significant to the intra-industry information diffusion of China's stock market, which generates more friction regarding intra-industry information diffusion.

Finally, this paper provides policy implications to policy considerations and market mechanisms. The impact of policy changes on information diffusion is one of the impacts of policy changes on financial market. Based on the split share structure reform and lifting short sale constraints, this paper suggests that these policy changes in China stock market impede the process of intra-industry information diffusion and they seem ineffective in some degree. Institutional frictions are accountable for producing the delay in the process of information diffusion. Thus, comprehending the process of information diffusion is very significant for policy considerations. Institutional reforms in China's stock market have been implemented for many years since the establishment of the market. However, the effectiveness of the policy changes is still in dispute. Policy considerations and market mechanisms in China should keep pace with the times, which could, in turn, facilitate that stock prices to develop more effectively and informatively. Nevertheless, policy considerations, especially in China, seldom consider the effectiveness and informativeness of stock prices, as well as the principle of gradual information diffusion when policies are formulated. Therefore, smoothing the process of intra-industry information diffusion and augmenting the market efficiency should be included into policy-making in the future.

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Variance and Dimension Reduction Monte Carlo Method for Pricing European Multi-Asset Options with Stochastic Volatilities

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Abstract: Pricing multi-asset options has always been one of the key problems in financial engineering because of their high dimensionality and the low convergence rates of pricing algorithms. This paper studies a method to accelerate Monte Carlo (MC) simulations for pricing multi-asset options with stochastic volatilities. First, a conditional Monte Carlo (CMC) pricing formula is constructed to reduce the dimension and variance of the MC simulation. Then, an efficient martingale control variate (CV), based on the martingale representation theorem, is designed by selecting volatility parameters in the approximated option price for further variance reduction. Numerical tests illustrated the sensitivity of the CMC method to correlation coefficients and the effectiveness and robustness of our martingale CV method. The idea in this paper is also applicable for the valuation of other derivatives with stochastic volatility.

Keywords: conditional Monte Carlo; variance reduction; multi-asset options; stochastic volatility; martingale control variate

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1. Introduction

In the last 40 years, financial derivatives have become increasingly important in finance. They are actively traded on many exchanges throughout the world, and are entered into by financial institutions, fund managers, and corporate treasurers in the over-the-counter market. They are especially important for market anticipants because they can be used to transfer a wide range of risks in the economy from one entity to another. Efficient use of financial derivatives can certainly promote financial and social sustainability. For instance, there are many different types of energy and agricultural commodity derivatives that are designed and used to contest weather and market risks, and to protect the benefit and reduce the potential loss of anticipants. Another example is that the real options approach is very popular in valuing the real estate sustainable investment. Conversely, inappropriate use of derivatives may cause great, even global, disasters, for example, the credit crisis that started in 2007. As pointed out by Hull [1], "we have now reached the stage where those who work in finance, and many who work outside finance, need to understand how derivatives work, how they are used, and how they are priced."

The accurate and fast pricing of financial derivatives is one of the most important things in financial engineering since many of the problems in economics and finance eventually turn into the pricing of financial derivatives. For example, Kim et al. [2] decided the optimal investment timing using rainbow options valuation for economic sustainability appraisement. Yoo et al. [3] determined an optimum combination of financial models including options to achieve a sustainable profit for overseas investment projects. The pioneering work of Black and Scholes [4] and Merton [5] lay the foundations for option pricing models. It is well known that the stochastic volatility model can be used to generalize the constant volatility assumption in the Black–Scholes model to capture the character of empirical observations from financial markets, such as the observed volatility smile and the leptokurtic features of the asset return distribution [6,7]. Stochastic volatility models describe volatility behavior with another stochastic differential equation. There are many studies on stochastic volatility models, such as those of Hull and White [8], Scott [9], Stein and Stein [10], Ball and Roma [11], Heston [12], Schöbel and Zhu [13], and Hagan et al. [14]. In addition to these one-factor stochastic volatility models, Fouque et al. [15–18] proposed a multi-factor mean-reverting stochastic volatility model. A comprehensive treatment of stochastic volatility models can be found in Reference [19].

Multi-asset options refer to a wide variety of contingent claims whose payoff depends on the overall performance of more than one underlying asset. Usually, they can be grouped into three categories: rainbow options, basket options, and quanto options. The prices of rainbow options rely on price changes of underlying assets, such as exchange options, outperformance options, spread options, chooser options, max-call options, and their variations. Basket options prices are always determined by the average price of underlying assets, while the value of a quanto option depends on the performance of domestic and foreign underlying assets. Jiang [20] introduced the concepts and constructed the pricing models of multi-asset options in detail, where the volatilities were constant. The pricing problem of multi-asset options pricing is essentially equivalent to a high dimensional integral. It is challenging to compute such a high dimensional integral, especially when the number of underlying assets is large, or stochastic volatilities are considered in the model.

There are mainly three pricing methods for multi-asset options: the analytic approximation method, the fast Fourier transformation (FFT) method, and the MC simulation method. The analytic approximation method typically constructs an approximate pricing model for the original problem that results in a closed form solution, and this method is always elegantly designed to the original problem. Several studies focus on this approach, for instance, those by Turnbull and Wakeman [21], Curran [22], Milevsky and Posner [23], Ju [24], Zhou and Wang [25], Alexander and Venkatramanan [26], Datey et al. [27], Brigo et al. [28], Borovkova et al. [29], Deelstra et al. [30,31], and Li et al. [32]. The main disadvantage of the analytic approximation method is that the size of the error is unknown and there is no way to systematically reduce it. The FFT method, which was prosed by Carr and Madan [33], has successfully been used in option pricing problems with a low dimension because of its high efficiency (see Carr and Wu [34], Heston [12], Grzelak et al. [35–37], and He and Zhu [38]). However, the FFT method depends on the availability of a characteristic function (usually in an affine framework), which is not always promised in a general stochastic volatility model. It is also difficult to apply the FFT method to high dimensional problems due to their dimensionality. Thus, for higher dimensional options, the most practical method seems to be MC simulations. Kim et al. [2] and Yoo et al. [3] also used MC simulations to price the embedded option prices in valuation real investment projects since the high dimension of problem. MC uses the sample mean as an estimator for the expectation of a random variable. Its speed of convergence is not influenced by the dimension of the problem. In addition, it allows for a simple error bound, given by the central limit theorem.

The major drawback of an MC simulation is that its convergence rate is quite slow, that is, $O(m^{-1/2})$, where m is the number of samples in MC simulation. As a result, often the main challenge in developing an efficient MC method is to find an effective variance reduction technique. There are a lot of studies about how to improve the efficiency of an MC simulation, and we refer the reader to Glasserman [39] and relevant references therein for a detailed discussion on various variance reduction techniques. Kemna and Vorst [40] presented one of the classical works on accelerating MC simulations. They used the geometric average option as a CV to price the arithmetic average option, which proved to be very successful. For a European multi-asset option pricing problem, Barraquand [41] proposed a "quadratic resampling" method by matching the moments of the underlying assets to reduce the variance of the MC simulation. Pellizari [42] designed a CV method called mean Monte Carlo to gain variance reduction of an MC simulation. The key of their success was that a Black–Scholes formula could be obtained when all underlying assets except for one were replaced by their mean. Borogovac and Vakili [43] proposed a "database Monte Carlo" CV method that avoids computing the expectation of CV, but the database, constructed in advance, requires huge calculations. Dingeç and Hörmann [44] exploited the property that the geometric average price was larger than the arithmetic average price to construct a CV by conditioning the payoff on the assumption that the geometric average of all prices was larger than the strike price. The expectation of their CV was computed by numerical methods, and their numerical tests for Asian options and basket options showed a great accelerating effect on the MC simulations. Liang et al. [45] designed a CV for European multi-asset options based on principal component analysis. Sun and Xu [46] used the CMC method with the importance sampling technique to accelerate MC simulations for basket options. There are some other approaches to speed up MC simulations, such as the quasi-Monte Carlo method [39,47–52], and parallelized implementations of MC simulations on CPUs/GPUs [53–58].

However, there is little research on variance reduction of MC simulations in pricing multi-asset options with stochastic volatilities. Du et al. [59] proposed a variance reduction method in multi-asset options under stochastic volatility models by matching the moments of the volatilities. Although their method shows great variance reduction of MC simulations, there are some restrictions to it. (1) All underlying assets are assumed to be driven by one stochastic volatility factor, which is not reasonable in practice. A more reasonable model is to assume that each underlying asset is driven by its own stochastic volatility factor (see Antonelli et al. [60], Shiraya and Takahashi [61], and Park et al. [62]). (2) Their moment matching technique greatly depends on the Hull–White stochastic volatility model, and is not applicable to general stochastic volatility models. (3) They only conducted numerical tests for options with two assets, which is not general enough for most multi-asset options.

In this paper, we aim to develop an efficient dimension and variance reduction method for MC simulations in pricing European multi-asset options with general stochastic volatilities. In our pricing framework, the underlying asset is assumed to be driven by its own stochastic volatility process, and full correlations between factors are allowed. The stochastic volatility model, which could be the Hull–White [8] or Heston [12] models, is quite general, such that our pricing model has a wide range of applicability. Our dimension and variance reduction method is built on the idea developed by Liang and Xu [63], who designed a CMC simulation with martingale CV to price single-asset European options with stochastic volatility. Our main contributions are: (1) A CMC pricing framework is deduced for European multi-asset options with general stochastic volatility models, which results in dimension and variance reduction. (2) A martingale CV based on a martingale representation theorem is combined with the CMC to obtain further variance reduction of the MC simulations. (3) The algorithm was tested on typical multi-asset options, such as exchange options, basket options (which can be more than two assets), and quanto options, showing the broad applicability and high efficiency of our method.

The paper is organized as follows. In Section 2, we introduce the pricing model of multi-asset options with stochastic volatilities. In Section 3, we deduce the CMC pricing framework, prove the martingale presentation theorem, and construct the martingale CV in detail. We present numerical tests and their results in Section 4, to evaluate the efficiency of our proposed method. Finally, we conclude the paper in Section 5.

2. Pricing Model

In this section, we give the pricing model of multi-asset options with stochastic volatilities. Specifically, in a risk-neutral world, let $S_i(t)$ be the price of the ith underlying asset ($i = 1, 2, \cdots, n$) at time t, which we assume obeys the following stochastic differential equations:

$$\frac{dS_i(t)}{S_i(t)} = (r-\delta_i)dt + f_i(Y_i(t))dW_i(t), \tag{1}$$
$$dY_i(t) = \mu_i(t, Y_i(t))dt + g_i(t, Y_i(t))dZ_i(t), \tag{2}$$

where r is the constant risk-free interest rate and δ_i is the continuous dividend rate. Y_i is the stochastic variance, and the functions $f_i(y), \mu_i(t,y)$, and $g_i(t,y)$ determine the specific volatility model, which can be quite general. $dW_i(t)$, and $dZ_i(t)$ are standard Brownian noise terms, and the covariance between them is captured as follows:

$$\mathrm{cov}(dW_i(t), dW_j(t)) = \rho_{ij}dt, \quad i \neq j, \tag{3}$$
$$\mathrm{cov}(dW_i(t), dZ_i(t)) = \rho_i dt, \quad i = 1, 2, \cdots, n, \tag{4}$$
$$\mathrm{cov}(dW_i(t), dZ_j(t)) = 0, \quad i \neq j, \tag{5}$$
$$\mathrm{cov}(dZ_i(t), dZ_j(t)) = 0, \quad i \neq j. \tag{6}$$

where the correlation coefficients ρ_{ij}, ρ_i are constant.

Equation (3) indicates that the underlying assets are correlated. Equations (4) and (5) indicate that any underlying asset is driven by only one stochastic variance factor and is not directly affected by the other stochastic variance factors. Equation (6) indicates that the random stochastic variance factors are mutually independent, but this assumption could be relaxed allowing for correlated random processes. Several popular stochastic volatility models are collected in Table 1.

Table 1. Models of stochastic volatility.

Reference	ρ_i	$f_i(y)$	$\mu_i(t,y)$	$g_i(t,y)$
Hull–White [8]	0	$\sqrt{y}$	μy	σy
Scott [9]	0	e^y	$a(\theta - y)$	σ
Stein–Stein [10]	0	$\|y\|$	$a(\theta - y)$	σ
Ball–Roma [11]	0	$\sqrt{y}$	$a(\theta - y)$	$\sigma\sqrt{y}(2a\theta > \sigma^2)$
Heston [12]	$\neq 0$	$\sqrt{y}$	$a(\theta - y)$	$\sigma\sqrt{y}(2a\theta > \sigma^2)$
Hagan et al. [14]	$\neq 0$	y	0	σy

Notes: μ is the drift of Hull–White stochastic volatility model. σ is the volatility of stochastic volatility. a is the rate of mean reversion and θ is the long-term mean of stochastic volatility. All parameters μ, a, θ, σ here are constants. The functions $\mu_i(t,y), g_i(t,y)$ here have no explicit dependence of time t.

In the following, we introduce our notations for convenience. The underlying asset vector is $\boldsymbol{S}(t) = (S_1(t), \cdots, S_n(t))'$, and the stochastic variance vector is $\boldsymbol{Y}(t) = (Y_1(t), \cdots, Y_n(t))'$, where $'$ represents the transpose of a vector or matrix. Additionally, the correlation matrix is given by $\Gamma = (\rho_{ij})$.

Suppose the payoff function of the European multi-asset option at maturity T is given by:

$$h(S_1(T), S_2(T), \cdots, S_n(T)) =: h(\boldsymbol{S}(T)). \tag{7}$$

Denote $V(t, \boldsymbol{s}, \boldsymbol{y})$ as the value of a European multi-asset option with stochastic volatilities at time t; then, by the no-arbitrage pricing principle we obtain:

$$V(t, \boldsymbol{s}, \boldsymbol{y}) = E\left[e^{-r(T-t)}h(\boldsymbol{S}(T)) \mid \boldsymbol{S}(t) = \boldsymbol{s}, \boldsymbol{Y}(t) = \boldsymbol{y}]\right], \tag{8}$$

where $E[\cdot]$ is the expectation in a risk-neutral world. Given the initial asset price $\boldsymbol{S}(0)$ and initial variance $\boldsymbol{Y}(0)$, the European option price at the initial time is actually:

$$V(0, \boldsymbol{S}(0), \boldsymbol{Y}(0)) = E[e^{-rT}h(\boldsymbol{S}(T))]. \tag{9}$$

MC simulation can be used to compute the option price based on Equation (9) (please see Glasserman [39]). Suppose the number of samples in MC simulation is m. Firstly, for the jth sample, we need to simulate the processes of the Brownian motions $W_i^{(j)}(t)$ and $Z_i^{(j)}(t), i = 1, 2, \cdots, n$ to get the processes of $\boldsymbol{Y}^{(j)}(t)$ and $\boldsymbol{S}^{(j)}(t)$ and the discounted payoff $V^{(j)} = e^{-rT}h(\boldsymbol{S}^{(j)}(T)), j = 1, 2, \cdots, m$. Then, we average the samples of discounted payoff and use the sample mean $\overline{V} = \frac{1}{m}\sum_{j=1}^{m} V^{(j)}$ as an estimation of the option price. The law of large numbers guarantees the convergence of MC simulation. The central limit theorem guarantees that the standard error—the standard deviation of sample mean $\overline{V}$—from MC simulation has a form of $Std = \frac{\mathrm{var}(V^{(j)})}{\sqrt{m}}$. The standard error can be used to measure how far the sample mean is likely to be from the option price or to make confidence intervals of the option price, for instance, a 95% confidence interval $\overline{V} \pm 1.96Std$. It also indicates that the MC simulation has a convergence rate as $O(m^{-1/2})$, which is rather low. Thus, in the next section, using a similar idea as in Liang and Xu [63], we propose our efficient CMC simulation framework with martingale CV for this option pricing problem.

If the stochastic volatility $f_i(Y_i(t))$ in Equation (1) is replaced by a constant volatility σ_i, we can obtain the dynamic process of an underlying asset with constant volatility as follows:

$$\frac{dS_i(t)}{S_i(t)} = (r - \delta_i)dt + \sigma_i dW_i(t), \quad i = 1, 2, \cdots, n. \tag{10}$$

The correlations between $dW_i(t)$ are defined by Equation (3). Jiang [20] carefully studied the explicit expression for a European multi-asset option value with constant volatility. Denote $V^{\mathrm{BS}}(t, \boldsymbol{S}(t); \boldsymbol{\sigma}, \Gamma)$ as the corresponding price at time t, where the volatility vector is $\boldsymbol{\sigma} = (\sigma_1, \sigma_2, \cdots, \sigma_n)'$. However, an analytic solution exists only for some specific options [20], such as exchange options, outer performance options, spread options, two dimension chooser options, basket options with a geometric average price, and quanto options. We give the specific expression for some of these in the numerical tests.

3. Dimension and Variance Reduction

In this section, we apply the acceleration methods of Liang and Xu [63] to price European multi-asset options with stochastic volatilities. The idea is that a martingale CV can be combined with the CMC method to reduce the variance of an MC simulation.

3.1. CMC Method

CMC can be used to reduce the variance of an MC simulation. Willard [64] initially put forward the CMC simulation to price options with stochastic volatilities. His method is feasible for those options that have a closed-form solution under the constant volatility model. Drimus [65] used CMC to analyze the variance products under the log-Ornstein–Uhlenbeck (log-OU) model. Boyle et al. [66] also used the CMC approach in pricing a down-and-in call option with a discretely monitored barrier. Broadie and Kaya [67] applied the CMC to accelerate exact simulations of the stochastic volatility with affine jump diffusion processes. Yang et al. [68] employed the CMC to reduce the variance of MC simulations when calculating the prices and greeks of barrier options. Dingeç and Hörmann [44] and Sun and Xu [46] combined CMC simulations and other variance reduction techniques to price basket options.

When we consider computing the expectation $E[Y]$ of a random variable Y, the conditional expectation $E[Y|X]$ of Y on some other variable X is also an unbiased estimator of $E[Y]$. This results from the double expectation formula $E[Y] = E\left[E[Y|X]\right]$, and the variance decomposition formula [69]:

$$\mathrm{var}(Y) = \mathrm{var}\left(E[Y|X]\right) + E[\mathrm{var}(Y|X)] \geq \mathrm{var}(E[Y|X]),$$

which indicates that the variance of $E[Y|X]$ is always smaller than that of Y. The so-called CMC method uses the conditional expectation of the random variable $E[Y|X]$ instead of that of the original random variable Y, which can obviously reduce variance. The key is that we need to have a closed form of $E[Y|X]$.

Now, we intend to deduce the CMC pricing formula for the pricing problem of Equation (8). The most important thing is to obtain the conditional expectation of the discounted payoff $e^{-rT}h(\boldsymbol{S}(T))$ on other random variables or stochastic information. First, a Cholesky decomposition of Brownian noise $dW_i(t)$ is conducted according to Equation (4):

$$dW_i(t) = \rho_i dZ_i(t) + \sqrt{1-\rho_i^2}d\tilde{Z}_i(t), \quad (i = 1, 2, \cdots, n), \tag{11}$$

where $dZ_i(t)$ and $d\tilde{Z}_i(t)$ are independent standard Brownian noises, which means that:

$$\text{cov}(dZ_i(t), d\tilde{Z}_i(t)) = 0, \quad (i = 1, 2, \cdots, n). \tag{12}$$

If we denote the vectors $d\boldsymbol{W}(t) = (dW_1(t), \cdots, dW_n(t))'$, $d\boldsymbol{Z}(t) = (dZ_1(t), \cdots, dZ_n(t))'$, and $d\tilde{\boldsymbol{Z}}(t) = (d\tilde{Z}_1(t), \cdots, d\tilde{Z}_n(t))'$, then Equation (11) can be rewritten to:

$$d\boldsymbol{W}(t) = diag(\boldsymbol{\rho})d\boldsymbol{Z}(t) + diag(\boldsymbol{q})d\tilde{\boldsymbol{Z}}(t). \tag{13}$$

where $\boldsymbol{\rho} = (\rho_1, \cdots, \rho_n)'$, $\boldsymbol{q} = \left(\sqrt{1-\rho_1^2}, \cdots, \sqrt{1-\rho_n^2}\right)'$, and $diag(\boldsymbol{v})$ is a diagonal matrix, with diagonal values from the vector $\boldsymbol{v}$. According to Equations (12) and (13), it is obvious that:

$$\text{cov}(d\boldsymbol{W}(t)) = diag(\boldsymbol{\rho})^2 dt + diag(\boldsymbol{q})\text{cov}(d\tilde{\boldsymbol{Z}}(t))diag(\boldsymbol{q}). \tag{14}$$

Notice that Equation (3) implies:

$$\text{cov}(d\boldsymbol{W}(t)) = \Gamma dt. \tag{15}$$

We can solve for the covariance of $d\tilde{\boldsymbol{Z}}(t)$ by Equations (14) and (15) as:

$$\text{cov}(d\tilde{\boldsymbol{Z}}(t)) = diag(\boldsymbol{q})^{-1}\left(\Gamma - diag(\boldsymbol{\rho})^2\right)diag(\mathbf{q})^{-1}dt =: \tilde{\Gamma}dt. \tag{16}$$

The entries of matrix $\tilde{\Gamma}$ are

$$\tilde{\Gamma}_{ii} = 1, \quad \tilde{\Gamma}_{ij} = \frac{\rho_{ij}}{\sqrt{1-\rho_i^2}\sqrt{1-\rho_j^2}} \quad (i \neq j). \tag{17}$$

To ensure the matrix $\tilde{\Gamma}$ is well-defined, the condition of correlation coefficients $|\rho_i| < 1, |\tilde{\Gamma}_{ij}| < 1$ should be satisfied.

Then, applying the Itô formula to $\ln(S_i(t))$, with the help of Equations (1) and (11), results in:

$$d\ln(S_i(t)) = \left(r - \delta_i - \tfrac{1}{2}f_i^2(Y_i(t))\right)dt + \rho_i f_i(Y_i(t))dZ_i(t) + \sqrt{1-\rho_i^2}f_i(Y_i(t))d\tilde{Z}_i(t), \quad (i = 1, 2, \cdots, n). \tag{18}$$

Integrating both sides of the above equation from t to T results in:

$$S_i(T) = S_i(t)\xi_i(t,T)\exp\left((r-\delta_i)(T-t) - \tfrac{1-\rho_i^2}{2}\int_t^T f_i^2(Y_i(s))ds + \sqrt{1-\rho_i^2}\int_t^T f_i(Y_i(s))d\tilde{Z}_i(s)\right), \tag{19}$$

where

$$\xi_i(t,T) = \exp\left(-\frac{1}{2}\rho_i^2\int_t^T f_i^2(Y_i(s))ds + \rho_i\int_t^T f_i(Y_i(s))dZ_i(s)\right). \tag{20}$$

Note that $\xi_i(t,T)$ is actually an exponential martingale with expectation $E[\xi_i(t,T)] = 1$.

Let $\bar{\sigma}_i(t,T)$ denote the average volatility of underlying asset S_i on the interval $[t,T]$, which is given by:

$$\bar{\sigma}_i(t,T)^2 = \frac{1}{T-t}\int_t^T f_i^2(Y_i(s))ds. \tag{21}$$

It is observed that, given the information of stochastic processes $\{Z_1(t), Z_2(t), \cdots, Z_n(t)\}$, the quantities $\xi_i(t,T)$, and $\bar{\sigma}_i(t,T)(i = 1, 2, \cdots, n)$ are totally determined. The pricing problem of Equation (8) then becomes the expectation of random variables $\{\tilde{Z}_1(t), \tilde{Z}_2(t), \cdots, \tilde{Z}_n(t)\}$. Assume there exists a Black–Scholes formula with constant volatilities. Then, calculating expectations with $\{\tilde{Z}_1(t), \tilde{Z}_2(t), \cdots, \tilde{Z}_n(t)\}$ gives us the CMC pricing formula of a European multi-asset option with stochastic volatility, as follows:

$$V(t, \boldsymbol{S}(t), \boldsymbol{Y}(t)) = E\left[V^{\mathrm{BS}}\left(t, \boldsymbol{S}(t) \cdot \boldsymbol{\xi}(t,T); \boldsymbol{q} \cdot \bar{\boldsymbol{\sigma}}(t,T), \tilde{\Gamma}\right)\right]. \tag{22}$$

where $\cdot$ is the dot product of two vectors, $\boldsymbol{\xi}(t,T) = (\xi_1(t,T), \cdots, \xi_n(t,T))'$, and $\bar{\boldsymbol{\sigma}}(t,T) = (\bar{\sigma}_1(t,T), \cdots, \bar{\sigma}_n(t,T))'$.

Compared with the MC formula in Equation (8), we now only need to simulate the n random variables $\{\boldsymbol{Z}(t)\}$ instead of the $2n$ random variables $\{\boldsymbol{W}(t)$, and $\boldsymbol{Z}(t)\}$. Thus, the dimension and variance are reduced by the properties of the CMC.

3.2. Martingale Control Variate (CV)

To further reduce the simulation variance of the variable $V^{\mathrm{BS}}\left(t, \boldsymbol{S}(t) \cdot \boldsymbol{\xi}(t,T); \boldsymbol{q} \cdot \bar{\boldsymbol{\sigma}}(t,T), \tilde{\Gamma}\right)$ in Equation (22), a general martingale CV is proposed to combine with the CMC simulation. Some brief introductions about the CV method are given at first (for more details and references, please refer to Glasserman [39]).

When the CV method is used to compute the expectation $E[Y]$, the CV estimator is:

$$Y(b) = Y - b(X - E[X]),$$

where X is called a CV and $E[X]$ is the closed-form expectation of X. The constant b can be selected as $b^* = \mathrm{cov}(X,Y)/\mathrm{var}(X)$ to minimize the variance of the CV estimator with an optimal variance reduction ratio $R^2 = \mathrm{var}(Y)/\mathrm{var}(Y(b^*)) = 1/(1-\rho^2_{XY})$. The efficiency of the CV method can be measured by the variance reduction ratio R^2 or the standard error reduction ratio R. The success of the CV depends on high correlations with the naive variable Y and the availability of its expectation $E[X]$. Thus, the CV is always elegantly designed to a specific problem. In this paper, a martingale whose expectation equals to zero is used as a CV, which avoids any extra effort needed to obtain its expectation.

To construct an efficient CV in the CMC framework, a martingale representation theorem for the stochastic volatility pricing model of Equations (1) and (2) is proved in the following theorem.

Theorem 1 (Martingale Representation Theorem). *If the underlying assets satisfy Equations (1) and (2), the European multi-asset option price at the initial time $V(0, \boldsymbol{S}(0), \boldsymbol{Y}(0))$ with payoff $h(\boldsymbol{S}(T))$ can be expressed as:*

$$e^{-rT}h(\boldsymbol{S}(T)) - V(0, \boldsymbol{S}(0), \boldsymbol{Y}(0)) = \int_0^T e^{-rt}\left(\sum_{i=1}^n S_i(t) f_i(Y_i(t)) \frac{\partial V}{\partial S_i} dW_i(t) + \sum_{i=1}^n \mu_i(t, Y_i(t)) \frac{\partial V}{\partial Y_i} dZ_i(t)\right), \tag{23}$$

which can be rewritten in vector form as:

$$e^{-rT}h(\boldsymbol{S}(T)) - V(0, \boldsymbol{S}(0), \boldsymbol{Y}(0)) = \int_0^T e^{-rt}\left((\boldsymbol{S}(t) \cdot \boldsymbol{f}(\boldsymbol{Y}(t)) \cdot \nabla_{\boldsymbol{S}} V)' d\boldsymbol{W}(t) + (\boldsymbol{\mu}(t, \boldsymbol{Y}(t)) \cdot \nabla_{\boldsymbol{Y}} V)' d\boldsymbol{Z}(t)\right), \tag{24}$$

where $\boldsymbol{f}(\boldsymbol{Y}(t)) = (f_1(Y_1(t)), \cdots, f_n(Y_n(t)))'$, $\boldsymbol{\mu}(t, \boldsymbol{Y}(t)) = (\mu_1(t, Y_1(t)), \cdots, \mu_n(t, Y_n(t)))'$, $\nabla_{\boldsymbol{S}} V = (\frac{\partial V}{\partial S_1}, \cdots, \frac{\partial V}{\partial S_n})'$, and $\nabla_{\boldsymbol{Y}} V = (\frac{\partial V}{\partial Y_1}, \cdots, \frac{\partial V}{\partial Y_n})'$.

Proof. Applying Itô's formula to $e^{-rt}V(t, \boldsymbol{S}(t), \boldsymbol{Y}(t))$ yields:

$$d\left(e^{-rt}V(t, \boldsymbol{S}(t), \boldsymbol{Y}(t))\right) = e^{-rt}LVdt + e^{-rt}\left(\sum_{i=1}^n S_i(t) f_i(Y_i(t)) \frac{\partial V}{\partial S_i} dW_i(t) + \sum_{i=1}^n \mu_i(t, Y_i(t)) \frac{\partial V}{\partial Y_i} dZ_i(t)\right),$$

where

$$LV = \frac{\partial V}{\partial t} + \frac{1}{2}\sum_{i,j=1}^{n} \rho_{ij} S_i S_j f_i(Y_i) f_j(Y_j) \frac{\partial^2 V}{\partial S_i \partial S_j} + \sum_{i=1}^{n} \rho_i S_i f_i(Y_i) \mu_i(t, Y_i) \frac{\partial^2 V}{\partial S_i \partial Y_i}$$
$$+ \frac{1}{2}\sum_{i=1}^{n} g_i^2(t, Y_i) \frac{\partial^2 V}{\partial Y_i^2} + \sum_{i=1}^{n} (r - \delta_i) S_i f_i(Y_i) \frac{\partial V}{\partial S_i} + \sum_{i=1}^{n} \mu_i(t, Y_i) \frac{\partial V}{\partial Y_i} - rV.$$

Furthermore, $LV = 0$ because of the Feynman–Kac formula [69], and thus:

$$d\left(e^{-rt} V(t, \mathbf{S}(t), \mathbf{Y}(t))\right) = e^{-rt}\left(\sum_{i=1}^{n} S_i(t) f_i(Y_i(t)) \frac{\partial V}{\partial S_i} dW_i(t) + \sum_{i=1}^{n} \mu_i(t, Y_i(t)) \frac{\partial V}{\partial Y_i} dZ_i(t)\right).$$

Now, by integrating both sides of the above equation on the interval $[0, T]$, and noticing that $V(T, \mathbf{S}(T), \mathbf{Y}(T)) = h(\mathbf{S}(T))$, we obtain the conclusion of the martingale representation theorem. □

The martingale representation theorem gives us inspiration to construct efficient CVs. For simplicity, denote:

$$X = \int_0^T e^{-rt}\left((\mathbf{S}(t) \cdot \boldsymbol{f}(\mathbf{Y}(t)) \cdot \nabla_{\mathbf{S}} V)' d\mathbf{W}(t) + (\boldsymbol{\mu}(t, \mathbf{Y}(t)) \cdot \nabla_{\mathbf{Y}} V)' d\mathbf{Z}(t)\right), \tag{25}$$

The martingale expression in Equation (23) indicates that the variance of $e^{-rT} h(\mathbf{S}(T))$ in the MC simulation is totally determined by the martingale X. Thus, the martingale X plays the role of a perfect CV for an MC simulation. Fouque and Han [18] actually gave a similar representation in their work, and used the martingales as a CV to price single-asset options under a specific multi-factor stochastic volatility model. This can be understood in financial terminology. The martingale CV corresponds to a continuous delta hedge strategy taken by a trader who sells the option. The integrands of the martingale would, in theory, be the perfect delta hedges. Even though perfect replication by delta hedging under stochastic volatility models is impossible, the variance of replication error is directly related to the variance induced by the martingale CV method.

For the CMC pricing framework, taking the conditional expectation of both sides of Equation (23) based on the information $\{\mathbf{Z}(t), 0 \le t \le T\}$, results in:

$$V^{\mathrm{BS}}\left(t, \mathbf{S}(t) \cdot \boldsymbol{\xi}(t, T); \boldsymbol{q} \cdot \bar{\boldsymbol{\sigma}}(t, T), \tilde{\Gamma}\right) - V(0, \mathbf{S}_0, \mathbf{Y}_0) = \hat{X}, \tag{26}$$

where

$$\hat{X} = E\left[X | \mathbf{Z}(t), 0 \le t \le T\right]. \tag{27}$$

We can determine the expression for $\hat{X}$ by first substituting the Cholesky decomposition, Equation (11), into the expression of X in Equation (25). Then, we compute the expectations about $\{\tilde{Z}_1(t), \tilde{Z}_2(t), \cdots, \tilde{Z}_n(t)\}$ as:

$$\hat{X} = \int_0^T e^{-rt} (\boldsymbol{\rho} \cdot \boldsymbol{F}_1(t))' d\mathbf{Z}(t) + \int_0^T e^{-rt} \boldsymbol{F}_2(t)' d\mathbf{Z}(t), \tag{28}$$

where

$$\boldsymbol{F}_1(t) = E[\mathbf{S}(t) \cdot \boldsymbol{f}(\mathbf{Y}(t)) \cdot \nabla_{\mathbf{S}} V | \mathbf{Z}(s), 0 \le s \le t], \tag{29}$$
$$\boldsymbol{F}_2(t) = E[\boldsymbol{\mu}(t, \mathbf{Y}(t)) \cdot \nabla_{\mathbf{Y}} V | \mathbf{Z}(s), 0 \le s \le t]. \tag{30}$$

Equation (26) shows that the variance of $V^{\mathrm{BS}}\left(t, \mathbf{S}(t) \cdot \boldsymbol{\xi}(t, T); \boldsymbol{q} \cdot \bar{\boldsymbol{\sigma}}(t, T), \tilde{\Gamma}\right)$ is totally determined by the zero martingale $\hat{X}$, since $V(0, \mathbf{S}_0, \mathbf{Y}_0)$ is a constant. This indicates that $\hat{X}$, theoretically, is a perfect CV for $V^{\mathrm{BS}}\left(t, \mathbf{S}(t) \cdot \boldsymbol{\xi}(t, T); \boldsymbol{q} \cdot \bar{\boldsymbol{\sigma}}(t, T), \tilde{\Gamma}\right)$ in CMC simulations. It is a pity that we have no explicit expression of this perfect zero martingale, since there is no exact expression for $V(t, \boldsymbol{s}, \boldsymbol{y})$. A possible solution is that we approximate the option price $V(t, \boldsymbol{s}, \boldsymbol{y})$ with a Black–Scholes option price along with some carefully selected volatility parameters. In the following, we show our approach.

Given the information $\{\boldsymbol{Z}(s), 0 \leq s \leq t\}$, the conditional expectation of $\boldsymbol{S}(t)$ can be computed by Equation (19) as:

$$\hat{\boldsymbol{S}}(t) = E[\boldsymbol{S}(t)|\boldsymbol{Z}(s), 0 \leq s \leq t] = e^{(r-\delta)t}\boldsymbol{S}(0) \cdot \boldsymbol{\xi}(0, t). \tag{31}$$

We intend to use $V^{\mathrm{BS}}(t, \boldsymbol{S}(t); \boldsymbol{\theta}, \Gamma)$ as an approximation of $V(t, \boldsymbol{S}(t), \boldsymbol{Y}(t))$, where $\boldsymbol{\theta}$ is a constant vector whose values should be carefully selected. The partial derivatives can thus be approximated as:

$$\begin{aligned} \nabla_{\boldsymbol{S}} V(t, \boldsymbol{S}(t), \boldsymbol{Y}(t)) &\approx \nabla_{\boldsymbol{S}} V^{\mathrm{BS}}(t, \boldsymbol{S}(t); \boldsymbol{\theta}, \Gamma), \\ \nabla_{\boldsymbol{Y}} V(t, \boldsymbol{S}(t), \boldsymbol{Y}(t)) &\approx \nabla_{\boldsymbol{Y}} V^{\mathrm{BS}}(t, \boldsymbol{S}(t); \boldsymbol{\theta}, \Gamma) = \boldsymbol{0}. \end{aligned}$$

Now, given the information $\{\boldsymbol{Z}(s), 0 \leq s \leq t\}$, by using the approximated derivatives and substituting $\boldsymbol{S}(t)$ with $\hat{\boldsymbol{S}}(t)$ in Equations (29) and (30), $\boldsymbol{F}_1(t)$ can be approximately expressed as:

$$\hat{\boldsymbol{F}}_1(t) = \hat{\boldsymbol{S}}(t) \cdot \boldsymbol{f}(\boldsymbol{Y}(t)) \cdot \nabla_{\boldsymbol{S}} V^{\mathrm{BS}}(t, \hat{\boldsymbol{S}}(t); \boldsymbol{\theta}, \Gamma). \tag{32}$$

Notice that $\nabla_{\boldsymbol{Y}} V^{\mathrm{BS}}(t, \hat{\boldsymbol{S}}(t); \boldsymbol{\theta}, \Gamma) = \boldsymbol{0}$, so $\hat{\boldsymbol{F}}_2(t) \approx \boldsymbol{0}$.

In the end, we obtain our martingale CV:

$$\tilde{X} = \int_0^T e^{-rt}(\boldsymbol{\rho} \cdot \hat{\boldsymbol{F}}_1(t))' d\boldsymbol{Z}(t). \tag{33}$$

The value of the constant volatility vector $\boldsymbol{\theta}$ should be determined if we want to use the martingale $\tilde{X}$ as a CV. Fouque and Han [18] illustrated a method for pricing a single-asset option with multi-factor volatility. They picked the long-term mean of the volatility as the volatility parameter in their specific multi-factor model. However, they did not offer a solution for non-mean-reverting stochastic volatility models, such as the Hull–White model.

In this paper, we set parameter $\boldsymbol{\theta} = \boldsymbol{f}(E[\boldsymbol{Y}(t)])$. The idea is that, on the interval $[t, T]$, the stochastic variance $\boldsymbol{Y}(t)$ is approximated by the expectations of their initial state $E[\boldsymbol{Y}(t)]$. This results in a corresponding approximated stochastic volatility $\boldsymbol{f}(E[\boldsymbol{Y}(t)])$. We hope that the dynamic behavior of the approximated process with such parameters is similar to the original process.

Remark 1. *It is difficult to use the CMC pricing formula of Equation (22) if the analytic solution of a European multi-asset option price under constant volatility does not exist. However, we can still construct a martingale CV for an MC simulation in those cases.*

According to the martingale representation theorem (Theorem 1), the variance of $e^{-rT}h(\boldsymbol{S}(T))$ in an MC simulation is totally determined by the zero martingale X (see Equation (23)). We can select a value $V^{\mathrm{approx}}(t, \boldsymbol{S}(t); \boldsymbol{\theta}, \Gamma)$ with a constant volatility parameter $\boldsymbol{\theta}$ as the approximation of option price $V(t, \boldsymbol{S}(t), \boldsymbol{Y}(t))$ under a stochastic volatility model. Following the idea in the CMC framework, we select $\boldsymbol{\theta} = \boldsymbol{f}(E[\boldsymbol{Y}(t)])$. Thus, the partial derivatives can be approximated as:

$$\begin{aligned} \nabla_{\boldsymbol{S}} V(t, \boldsymbol{S}(t), \boldsymbol{Y}(t)) &\approx \nabla_{\boldsymbol{S}} V^{\mathrm{approx}}(t, \boldsymbol{S}(t); \boldsymbol{\theta}, \Gamma), \\ \nabla_{\boldsymbol{Y}} V(t, \boldsymbol{S}(t), \boldsymbol{Y}(t)) &\approx \nabla_{\boldsymbol{Y}} V^{\mathrm{approx}}(t, \boldsymbol{S}(t); \boldsymbol{\theta}, \Gamma) = 0. \end{aligned}$$

Furthermore, the martingale CV is:

$$\tilde{X} = \int_0^T e^{-rt}\left(\boldsymbol{\rho} \cdot \boldsymbol{S}(t) \cdot \boldsymbol{f}(\boldsymbol{Y}(t)) \cdot \nabla_{\boldsymbol{S}} V^{\mathrm{approx}}(t, \boldsymbol{S}(t); \boldsymbol{\theta}, \Gamma)\right)' d\boldsymbol{Z}(t).$$

Taking the arithmetic average basket option with stochastic volatilities as an example, we can use the geometric average basket option with constant volatilities as an approximation and then construct the *corresponding CV. It is expected that, for a more accurate approximated price $V^{\text{approx}}(t, \boldsymbol{S}(t); \boldsymbol{\theta}, \Gamma)$, a larger variance reduction ratio can be obtained by the corresponding martingale CV.*

4. Numerical Tests

In this section, we present some numerical tests designed for the typical multi-asset options—including the exchange options, basket options and quanto options—to emphasize the efficiency of our method.

4.1. Exchange Options

The exchange option, which was first studied by Margrabe [70], empowers its holder with the right to exercise it by comparing the difference between the prices or the rates of return of two underlying assets. Its payoff is:

$$h^{\text{excha}}(S_1(T), S_2(T)) = \max(S_2(T) - S_1(T), 0). \tag{34}$$

If the underlying assets evolute with constant volatilities σ_1 and σ_2, the exchange option has a pricing formula at time t, as shown by Margrabe [70] and Jiang [20] as follows:

$$V^{\text{BS-excha}}(t, S_1, S_2) = e^{-\delta_2(T-t)} S_2 N(-d_2) - e^{-\delta_1(T-t)} S_1 N(-d_1), \tag{35}$$

where

$$\begin{aligned} d_1 &= \frac{\ln \frac{S_1}{S_2} + \left(\delta_2 - \delta_1 + \frac{1}{2}(\sigma_1^2 - 2\rho_{12}\sigma_1\sigma_2 + \sigma_2^2)\right)(T-t)}{\sqrt{(\sigma_1^2 - 2\rho_{12}\sigma_1\sigma_2 + \sigma_2^2)(T-t)}}, && (36) \\ d_2 &= d_1 - \sqrt{(\sigma_1^2 - 2\rho_{12}\sigma_1\sigma_2 + \sigma_2^2)(T-t)}, && (37) \end{aligned}$$

and $N(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-\frac{t^2}{2}} dt$ is the cumulative distribution function of a standard normal variable. It is easy to derive the derivatives:

$$\begin{aligned} \frac{\partial}{\partial S_1} V^{\text{BS-excha}}(t, S_1, S_2) &= -e^{-\delta_1(T-t)} N(-d_1), \\ \frac{\partial}{\partial S_2} V^{\text{BS-excha}}(t, S_1, S_2) &= e^{-\delta_2(T-t)} N(-d_2). \end{aligned}$$

We assumed the stochastic volatilities obey the Heston model, for $i = 1, 2$:

$$\begin{aligned} \frac{dS_i(t)}{S_i(t)} &= (r - \delta_i)dt + \sqrt{Y_i(t)} dW_i(t), \\ dY_i(t) &= a_i(\theta_i - Y_i(t))dt + \sigma_i \sqrt{Y_i(t)} dZ_i(t). \end{aligned}$$

The parameters should satisfy the Feller condition [71] to guarantee the positiveness of variance, i.e., $2a_1\theta_1 > \sigma_1^2$ and $2a_2\theta_2 > \sigma_2^2$. We used a truncated Euler discrete scheme [39,72,73] with equal time intervals to simulate the Heston process in our tests.

At first, we wanted to examine the acceleration effect of a CMC simulation compared with a traditional MC simulation. We fixed the parameters $S_1(0) = S_2(0) = K = 30$, $r = 0.05$, $T = 1$, $\delta_1 = \delta_2 = 0$, $a_1 = a_2$, $\sigma_1 = \sigma_2 = 0.2$, $Y_1(0) = 0.01$, $Y_2(0) = 0.04$, $\theta_1 = 0.015$, and $\theta_2 = 0.05$. Additionally, we took the number of time steps $N = 100$, and the number of simulations $m = 100{,}000$ in all numerical simulations. Note that $\left| \frac{\rho_{12}}{\sqrt{1-\rho_1^2}\sqrt{1-\rho_2^2}} \right| < 1$ should be satisfied from Equation (17).

Taking $\rho_{12} = 0$ for simplicity, the numerical results with different correlation coefficients are recorded in Tables 2 and 3.

Table 2. Exchange option: Estimated prices for MC and CMC with different correlation coefficients.

$\rho_1 \vert \rho_2$	**−0.75**	**−0.50**	**−0.25**	**0.00**	**0.25**	**0.50**	**0.75**	
−0.75	2.8083	2.8218	2.8336	2.8436	2.8519	2.8587	2.8639	
−0.50	2.8169	2.8294	2.8402	2.8493	2.8567	2.8623	2.8663	
−0.25	2.8248	2.8362	2.8459	2.8539	2.8603	2.8649	2.8678	
0.00	2.8317	2.8420	2.8505	2.8573	2.8625	2.8661	2.8680	$\overline{V}_{\mathrm{MC}}$
0.25	2.8372	2.8462	2.8536	2.8594	2.8635	2.8660	2.8667	
0.50	2.8413	2.8492	2.8554	2.8600	2.8630	2.8644	2.8641	
0.75	2.8440	2.8508	2.8558	2.8592	2.8612	2.8615	2.8601	
−0.75	2.8153	2.8294	2.8420	2.8528	2.8616	2.8684	2.8731	
−0.50	2.8253	2.8377	2.8486	2.8578	2.8651	2.8703	2.8735	
−0.25	2.8340	2.8446	2.8539	2.8615	2.8672	2.8709	2.8725	
0.00	2.8413	2.8503	2.8579	2.8639	2.8679	2.8700	2.8700	$\overline{V}_{\mathrm{CMC}}$
0.25	2.8473	2.8546	2.8606	2.8649	2.8674	2.8678	2.8661	
0.50	2.8519	2.8576	2.8620	2.8647	2.8654	2.8641	2.8608	
0.75	2.8550	2.8592	2.8620	2.8630	2.8621	2.8591	2.8539	

Notes: ρ_1 is the correlation coefficient between the first underlying asset and its volatility; ρ_2 is the correlation coefficient between the second underlying asset and its volatility; $\overline{V}_{\mathrm{MC}}$ is the estimated price for MC simulation; and $\overline{V}_{\mathrm{CMC}}$ is the estimated price for CMC simulation.

Table 3. Exchange option: Numerical results for MC and CMC with different correlation coefficients.

$\rho_1 \vert \rho_2$	**−0.75**	**−0.50**	**−0.25**	**0.00**	**0.25**	**0.50**	**0.75**	
−0.75	0.0132	0.0137	0.0143	0.0148	0.0153	0.0159	0.0164	
−0.50	0.0132	0.0137	0.0142	0.0148	0.0153	0.0158	0.0164	
−0.25	0.0131	0.0137	0.0142	0.0147	0.0153	0.0158	0.0164	
0.00	0.0131	0.0136	0.0141	0.0147	0.0152	0.0158	0.0163	Std_{MC}
0.25	0.0130	0.0135	0.0141	0.0146	0.0152	0.0157	0.0163	
0.50	0.0130	0.0135	0.0140	0.0146	0.0151	0.0157	0.0163	
0.75	0.0129	0.0134	0.0140	0.0145	0.0151	0.0156	0.0162	
−0.75	0.0088	0.0065	0.0049	0.0045	0.0058	0.0084	0.0119	
−0.50	0.0081	0.0055	0.0036	0.0032	0.0049	0.0077	0.0115	
−0.25	0.0076	0.0048	0.0025	0.0020	0.0042	0.0073	0.0112	
0.00	0.0074	0.0045	0.0019	0.0011	0.0039	0.0071	0.0110	Std_{CMC}
0.25	0.0075	0.0046	0.0020	0.0012	0.0039	0.0072	0.0111	
0.50	0.0078	0.0050	0.0027	0.0021	0.0043	0.0074	0.0113	
0.75	0.0084	0.0057	0.0036	0.0031	0.0048	0.0078	0.0116	
−0.75	1.5014	2.1268	2.9394	3.2711	2.6283	1.8898	1.3762	
−0.50	1.6372	2.4911	3.9677	4.6222	3.1339	2.0450	1.4323	
−0.25	1.7336	2.8222	5.5991	7.3682	3.6300	2.1571	1.4677	
0.00	1.7692	2.9943	7.3944	13.0340	3.9300	2.2070	1.4805	$R = \frac{Std_{\mathrm{MC}}}{Std_{\mathrm{CMC}}}$
0.25	1.7385	2.9276	7.0000	11.8935	3.8805	2.1900	1.4714	
0.50	1.6551	2.6807	5.2352	7.0184	3.5503	2.1170	1.4433	
0.75	1.5402	2.3701	3.9081	4.7380	3.1223	2.0066	1.4001	

Notes: ρ_1 is the correlation coefficient between the first underlying asset and its volatility; ρ_2 is the correlation coefficient between the second underlying asset and its volatility; Std_{MC}, Std_{CMC} are the standard errors of estimated prices from the MC and CMC simulations respectively; and $R = \frac{Std_{\mathrm{MC}}}{Std_{\mathrm{CMC}}}$ is the ratio of standard errors.

Table 2 records the estimated option values calculated by the MC and CMC simulations, which are denoted as $\overline{V}_{\mathrm{MC}}$ and $\overline{V}_{\mathrm{CMC}}$, respectively. The upper part of Table 3 records the standard errors of an MC simulation, denoted as Std_{MC}. The standard errors are almost the same for various correlation coefficients, and increase slightly with correlation ρ_2 while decreasing with ρ_1. The exchange option can be seen as a call option on asset S_2 for fixed S_1; a higher correlation ρ_2 implies a larger variation in the price of asset S_2, thus resulting in a larger value of the option price and a larger simulation variance. Similar analysis can be conducted with respect to correlation ρ_1 by regrading the exchange option as a put option on asset S_1 for fixed S_2.

The middle part of Table 3 records the standard errors of a CMC simulation, denoted as Std_{CMC}. Obviously, the standard CMC errors are always smaller than MC. It is interesting that a standard CMC error rapidly declines as correlation coefficient ρ_1 or ρ_2 tends to zero. Thus, the ratio of the standard errors of a CMC simulation to an MC simulation reduces. We denote this ratio as $R = Std_{\text{MC}}/Std_{\text{CMC}}$ and present its values at the bottom of Table 3. R becomes larger when the correlation coefficient is getting closer to the original point, and decays rapidly in the opposite direction. For example, for $\rho_1 = \rho_2 = 0, 0.25, 0.5$, and 0.75, the reduction ratios of the standard error are 13.0340, 3.8805, 2.1170, and 1.4001, respectively. This can be explained by Equation (11); the CMC simulation removes the randomness that is independent from the stochastic variances Y_1, Y_2, and its quantity is proportional to $\sqrt{1-\rho_1^2}$, or $\sqrt{1-\rho_2^2}$. In other words, a larger variance reduction ratio is promised when the absolute value of ρ_1 or ρ_2 is smaller. This property indicates that a CMC simulation is more competitive when the correlation between the underlying asset and stochastic volatility is weak.

We also investigated the computational costs of the MC and CMC methods. The computational platform for this paper was an Intel i5-6200U CPU, 2.30 GHz, 8 GB memory, and the software environment was Matlab R2018a for Windows 10. It took 50.88 s to calculate all of the data in the upper part of Table 3 and 25.85 s for the middle part, which means that the time cost of a CMC simulation is almost half that of an MC simulation. This is because the MC method needs to simulate four random variables, $\{W_1(t), W_2(t), Z_1(t)$, and $Z_2(t)\}$, while the CMC method only needs to simulate two random variables, $\{Z_1(t)$, and $Z_2(t)\}$.

Taking the variance reduction ratio into consideration, the speed up ratio of a CMC simulation to an MC simulation is defined as $\frac{Std^2_{\text{MC}}}{Std^2_{\text{CMC}}} \cdot \frac{t_{\text{MC}}}{t_{\text{CMC}}}$. Thus, when correlation $\rho_1 = \rho_2 = 0$, the speed up ratio of the CMC is $13.0340^2 \cdot \frac{50.88}{25.85} = 334.38$. Even for the case of a larger correlation $\rho_1 = \rho_2 = 0.75$, the speed up ratio of the CMC is $1.4001^2 \cdot \frac{50.88}{25.85} = 3.86$, which improves the efficiency of the MC simulation by roughly 75%. In summary, the CMC simulation enjoys the advantages of saving time and having a great variance reduction ratio, especially when the correlation coefficients are small.

We next tested the efficiency of our martingale CV method. As a contrast, we constructed another CV for the stochastic model, as suggested by Ma and Xu [74]. Consider dummy assets whose prices $\tilde{S}_i(t), (i = 1, 2, \cdots, n)$ satisfy the following stochastic differential equations:

$$\frac{d\tilde{S}_i(t)}{\tilde{S}_i(t)} = (r - \delta_i)dt + \tilde{\sigma}_i(t)dW_i(t),$$

where $\tilde{\sigma}_i(t)$ is a determined function. The covariance of $dW_i(t)$ is given by Equation (3). It can be computed by matching the first two moments of the underlying asset prices as $\tilde{\sigma}_i^2(t) = E[f_i^2(Y_i(t))]$. In the case of a Heston stochastic volatility model:

$$\tilde{\sigma}_i^2(t) = E[Y_i(t)] = \theta_i + (Y_i(0) - \theta_i)e^{-a_i t}, \quad i = 1, 2.$$

We used the payoff $h^{\text{excha}}(\tilde{S}_1(T), \tilde{S}_2(T))$ as a CV to the MC method, and we called this CV method a function CV method. The corresponding exchange option price can be computed using Equation (35) by replacing $\sigma_1^2 + \sigma_2^2 - 2\rho_{12}\sigma_1\sigma_2$ in Equations (36) and (37) with the average volatility on the interval $[0, T]$ given by:

$$\frac{1}{T}\int_0^T E[Y_1(t)] + E[Y_2(t)] - 2\rho_{12}\sqrt{E[Y_1(t)]E[Y_2(t)]}dt.$$

We changed the values of the correlation coefficients and kept the other parameters fixed as before. Remember that $\left|\frac{\rho_{12}}{\sqrt{1-\rho_1^2}\sqrt{1-\rho_2^2}}\right| < 1$. The detailed results are shown in Table 4.

Table 4. Exchange option: Numerical results for CVs with different correlation coefficients.

ρ_{12}	$\rho_1 = \rho_2$	Std_{MC}	Std_{Mar}	Std_{Fun}	R_1	R_2
−0.5	−0.6	0.0160	0.0015	0.0039	10.3761	4.1166
	−0.4	0.0163	0.0013	0.0040	12.2233	4.0626
	−0.2	0.0166	0.0012	0.0041	13.9129	4.0540
	0.0	0.0170	0.0011	0.0042	15.0719	4.0821
	0.2	0.0173	0.0013	0.0042	13.2504	4.1410
	0.4	0.0176	0.0016	0.0042	11.1433	4.2271
	0.6	0.0180	0.0019	0.0041	9.5880	4.3348
0.0	−0.75	0.0132	0.0014	0.0039	9.6978	3.4035
	−0.50	0.0137	0.0012	0.0040	11.2209	3.4318
	−0.25	0.0142	0.0010	0.0041	14.6458	3.4829
	0.00	0.0147	0.0009	0.0041	16.2942	3.5500
	0.25	0.0152	0.0011	0.0042	13.3596	3.6291
	0.50	0.0157	0.0015	0.0042	10.2764	3.7178
	0.75	0.0162	0.0017	0.0043	9.6550	3.8097
0.5	−0.6	0.0106	0.0010	0.0038	10.9374	2.8023
	−0.4	0.0110	0.0009	0.0040	12.9115	2.7755
	−0.2	0.0115	0.0006	0.0041	17.7294	2.7910
	0.0	0.0119	0.0006	0.0042	19.8106	2.8424
	0.2	0.0123	0.0008	0.0042	14.7523	2.9285
	0.4	0.0127	0.0012	0.0042	10.7868	3.0531
	0.6	0.0131	0.0012	0.0041	10.6183	3.2264

Notes: ρ_{12} is the correlation coefficient between the first underlying asset and the second underlying asset; ρ_1 is the correlation coefficient between the first underlying asset and its volatility; ρ_2 is the correlation coefficient between the second underlying asset and its volatility; Std_{MC}, Std_{Mar}, Std_{Fun} are the standard errors from the MC method, the martingale CV method and the function CV method respectively; $R_1 = Std_{\text{MC}}/Std_{\text{Mar}}$; and $R_2 = Std_{\text{MC}}/Std_{\text{Fun}}$.

In Table 4, Std_{MC}, Std_{Mar}, and Std_{Fun} are the standard errors from the MC simulation, the martingale CV method, and the function CV method, respectively. $R_1 = Std_{\text{MC}}/Std_{\text{Mar}}$ is the standard error reduction ratio of the martingale CV method compared to the MC simulation, and $R_2 = Std_{\text{MC}}/Std_{\text{Fun}}$ is the the standard error reduction ratio of the function CV method compared to the MC simulation.

It is obvious that the standard error reduction ratio of the CMC is much larger than that of the function CV method, the former falling in 9–20 while the latter being about 3 or 4. Table 4 also shows that, for a fixed $\rho_1 = \rho_2$, the standard errors of the MC simulation, martingale CV method, and function CV method decrease with the correlation value of ρ_{12}. For a fixed ρ_{12}, the standard errors of the MC simulation and function CV method increase with the value of $\rho_1 = \rho_2$ while the martingale CV method decreases with the absolute value of $\rho_1 = \rho_2$, which is mainly caused by the properties of the CMC. Thus, the standard error reduction ratio of the martingale CV method also decreases with the absolute value of $\rho_1 = \rho_2$.

The computing times for all values of the MC, the martingale CV, and the function CV methods are 22.33, 22.26, and 25.50 s, respectively. The time costs of the MC method and the martingale CV method are almost the same, while the function CV method is slightly slower. Thus, the martingale CV method proposed in our paper is superior to the function CV method, when considering the variance reduction ratio and the time cost.

Fixing the parameters $\rho_{12} = 0$, and $\rho_1 = \rho_2 = 0.5$, we next examined the effects of the volatility parameters for the stochastic volatility. In the Heston stochastic volatility model, the Feller condition should be satisfied [71]; thus, $\sigma_1 < \sqrt{2a_1\theta_1} = \sqrt{2 \cdot 2 \cdot 0.015} = 0.2449$, and $\sigma_2 < \sqrt{2a_2\theta_2} = \sqrt{2 \cdot 2 \cdot 0.05} = 0.4472$. Numerical results of these tests are shown in Table 5.

Table 5. Exchange option: Numerical results for CVs with different volatilities of the stochastic volatilities.

σ_1	σ_2	Std_{MC}	Std_{Mar}	Std_{Fun}	R_1	R_2
0.2	0.1	0.0151	0.0013	0.0030	11.7123	4.9767
	0.2	0.0157	0.0015	0.0042	10.2764	3.7178
	0.3	0.0163	0.0018	0.0057	9.0825	2.8678
	0.4	0.0169	0.0021	0.0073	8.1624	2.3279
0.05	0.2	0.0157	0.0014	0.0034	11.2239	4.5840
0.10		0.0157	0.0014	0.0036	10.9406	4.3545
0.15		0.0157	0.0015	0.0039	10.6170	4.0447
0.20		0.0157	0.0015	0.0042	10.2764	3.7178

Notes: σ_1 is the volatility of the first stochastic volatility; and σ_2 is the volatility of the second stochastic volatility.

As shown in Table 5, the standard errors of the three simulation methods all increase with increasing volatilities of stochastic volatilities. Standard error reduction ratios also decline with the volatility of the stochastic volatilities. However, our martingale CV method is much more efficient than the function CV method, especially in the case of large volatility.

4.2. Basket Options

The payoff of the basket option at maturity depends on the average price of the underlying assets. Since the basket option with arithmetic average price does not have a closed-form price, even with constant volatility, we considered the geometric average basket option whose payoff at time T is:

$$h^{\text{GeomBasket}}(\boldsymbol{S}(T)) = \max\left(\prod_{i=1}^{n} S_i^{\alpha_i}(T) - K, 0\right), \tag{38}$$

where n is the number of underlying assets, $\alpha_i \geq 0$ are the weights of each underlying asset with $\sum_{i=1}^{n} \alpha_i = 1$, and K is the strike price.

The geometric average basket option has a closed-form solution if the underlying assets have constant volatilities as $\sigma_1, \cdots, \sigma_n$. Denote:

$$\begin{aligned} \hat{\sigma}^2 &= \sum_{i,j=1}^{n} \alpha_i \alpha_j \sigma_i \sigma_j \rho_{ij}, \\ \hat{\delta} &= \sum_{i=1}^{n} \alpha_i \left(\delta_i + \frac{\sigma_i^2}{2}\right) - \frac{\hat{\sigma}^2}{2}. \end{aligned}$$

The geometric average basket option price at time t is given by Jiang [20]:

$$V^{\text{BS}-\text{GeomBasket}}(t, \boldsymbol{S}) = S_1^{\alpha_1} \cdots S_n^{\alpha_n} e^{-\hat{\delta}(T-t)} N(d_1) - K e^{-r(T-t)} N(d_2), \tag{39}$$

where

$$\begin{aligned} d_1 &= \frac{\ln \frac{S_1^{\alpha_1} \cdots S_n^{\alpha_n}}{K} + \left(r - \hat{\delta} + \frac{1}{2}\hat{\sigma}^2\right)(T-t)}{\hat{\sigma}\sqrt{T-t}}, \\ d_2 &= d_1 - \hat{\sigma}\sqrt{T-t}. \end{aligned}$$

Thus, the derivatives are:

$$\frac{\partial}{\partial S_j} V^{\text{BS}-\text{GeomBasket}}(t, \boldsymbol{S}) = e^{-\hat{\delta}(T-t)} N(d_1) \alpha_j S_j^{-1} \prod_{i=1}^{n} S_i^{\alpha_i}, \quad j = 1, 2, \cdots, n.$$

For a basket option with n underlying assets, we still used the Heston stochastic volatility model and function CV method as a comparison. The expectation of the corresponding CV can be calculated using Equation (39) by substituting $\sigma_i\sigma_j$ with $\frac{1}{T}\int_0^T \sqrt{E[Y_i(t)]E[Y_j(t)]}dt$. We fixed the parameters $r = 0.05$, $T = 1$, $K = 30$, $S_i(0) = 30$, $\delta_i = 0$, $a_i = 2$, and $\sigma_i = 0.2\,(i = 1, 2, \cdots, n)$. We allocated equal weights for the underlying assets, which means that $\alpha_i = 1/n$. For the initial value of the stochastic volatility, we took a linear interpolation between 0.1^2 and 0.3^2 for the n assets. In other words, the initial variance vector was $Y(0) = (0.1^2, 0.3^2)'$ for $n = 2$ and $Y(0) = (0.1^2, 0.15^2, 0.2^2, 0.25^2, 0.3^2)'$ for $n = 5$. We took the long-term mean of stochastic variance as $\theta_i = (\sqrt{Y_i(0)} + 0.05)^2$, which was $\theta = (0.15^2, 0.35^2)'$ for $n = 2$, for example. For the correlations between Brownian noises, we took $\rho_{ij} = \rho_0 (i \neq j)$ for simplicity. To guarantee the positive definiteness of the matrix $\Gamma = (\rho_{ij})$, the parameter ρ_0 should satisfy $-1/(n-1) < \rho_0 < 1$. In addition, $\left|\frac{\rho_{ij}}{\sqrt{1-\rho_i^2}\sqrt{1-\rho_j^2}}\right| < 1$ is needed for the proper definition of $\widetilde{\Gamma}$. Thus, we set $\rho_{ij} = \rho_0 = 0 (i \neq j)$ at first. We fixed the number of time steps to $N = 100$ and the number of simulations to $m = 100{,}000$. We tested the acceleration effects of the CVs for different correlation coefficients ρ_i. Numerical results are shown in Table 6.

Table 6. Geometric average basket option: Numerical results for CVs with different correlation coefficients.

n	ρ_i	Std_{MC}	Std_{Mar}	Std_{Fun}	R_1	R_2
2	−0.75	0.0110	0.0012	0.0021	9.2740	5.2542
	−0.50	0.0112	0.0009	0.0021	12.8705	5.2650
	−0.25	0.0115	0.0004	0.0022	27.4754	5.2935
	0.00	0.0117	0.0004	0.0022	30.5615	5.3375
	0.25	0.0120	0.0005	0.0022	23.5176	5.3968
	0.50	0.0122	0.0010	0.0022	11.9347	5.4719
	0.75	0.0124	0.0013	0.0022	9.2236	5.5629
5	−0.75	0.0068	0.0009	0.0013	7.6660	5.1178
	−0.50	0.0069	0.0006	0.0013	11.7653	5.1320
	−0.25	0.0069	0.0002	0.0013	27.9824	5.1434
	0.00	0.0070	0.0001	0.0014	110.3248	5.1544
	0.25	0.0071	0.0003	0.0014	25.1755	5.1663
	0.50	0.0071	0.0006	0.0014	11.1250	5.1785
	0.75	0.0072	0.0010	0.0014	7.4879	5.1952
10	−0.75	0.0049	0.0008	0.0010	6.3077	5.0690
	−0.50	0.0049	0.0005	0.0010	10.4984	5.0820
	−0.25	0.0049	0.0002	0.0010	26.5073	5.0928
	0.00	0.0050	1.7×10^{-5}	0.0010	291.4214	5.1023
	0.25	0.0050	0.0002	0.0010	24.2257	5.1104
	0.50	0.0050	0.0005	0.0010	10.0253	5.1192
	0.75	0.0050	0.0008	0.0010	6.1413	5.1310

Notes: n is number of underlying assets; and ρ_i is correlation coefficient between the ith underlying asset and its volatility.

Table 6 again shows that Std_{Mar}, the standard error of the martingale CV method, decreases as the correlation coefficients ρ_i tends to zero, resulting in a greater standard error reduction ratio R_1 in those cases. For example, R_1 goes from 30 to 9 when $|\rho_i|$ goes from 0 to 0.75. On the other hand, the simulation error Std_{Fun} and, thus, the corresponding reduction ratio R_2 of the function CV method are not sensitive to the correlation coefficient. The reduction ratio is around 5 in all cases. Considering the number of underlying assets, the reduction ratio of the martingale CV slightly decreases as the number of assets n becomes larger, except for the $\rho_i = 0$ cases. For example, the reduction ratios of the martingale CV method are 9.2740, 7.6660, and 6.3077 for $n = 2, 5$, and 10, respectively, and for $\rho_i = -0.75$. On the other hand, the ratios are 30.5615, 110.3248, and 291.4214 for the $\rho_i = 0$ case. As a contrast, the performance of the function CV method is more stable with different n. It is obvious that our martingale CV is much more efficient than the function CV method.

Next, we fixed $\rho_i = 0.5 (i = 1, 2, \cdots, n)$ and changed the value of σ_i, the volatility of the stochastic volatility. For convenience, we took an equal σ_i for every underlying asset. The results are recorded in Table 7.

Table 7. Geometric basket option: Numerical results for CVs with different volatilities of the stochastic volatility.

n	σ_i	Std_{MC}	Std_{Mar}	Std_{Fun}	R_1	R_2
2	0.1	0.0177	0.0013	0.0011	13.7479	15.6830
	0.2	0.0179	0.0013	0.0023	13.3158	7.9626
	0.3	0.0182	0.0014	0.0034	12.8095	5.4211
	0.4	0.0184	0.0015	0.0044	12.2580	4.1894
5	0.1	0.0093	0.0007	0.0006	12.7129	14.3708
	0.2	0.0093	0.0007	0.0013	12.4417	7.2688
	0.3	0.0094	0.0008	0.0019	12.1388	4.9147
	0.4	0.0094	0.0008	0.0025	11.8127	3.7571
10	0.1	0.0060	0.0005	0.0004	11.8384	13.8295
	0.2	0.0060	0.0005	0.0009	11.6365	6.9848
	0.3	0.0060	0.0005	0.0013	11.4192	4.7179
	0.4	0.0060	0.0005	0.0017	11.1910	3.5979

Notes: n is number of underlying assets; and σ_i is the volatility of the ith stochastic volatility.

As shown in Table 7, the standard errors of the three simulation methods increase with the volatilities of the stochastic volatility at fixed n, and decrease with the number of underlying assets for a fixed σ_i. The standard error reduction ratios of the two CV methods decrease with increasing volatility of the stochastic volatility and increasing number of assets. However, the martingale CV method is more robust for different volatilities compared to the function CV method. For example, for the case of $n = 2$, the standard error reduction ratio of the martingale CV method decreases from 13.7479 to 12.2580 when σ_i increases from 0.1 to 0.4, while that of the function CV method sharply decreases from 15.6830 to 4.1894. The results suggest that our martingale CV method is especially efficient in high volatility cases, while the function CV method has some advantages in a low volatility environment.

4.3. Quanto Options with Real Data

The quanto option is a contract written when someone invests money in foreign securities. Usually, its risk depends on the volatility of the securities' prices and the change of the foreign currency rate. Its main purpose is to provide exposure to a foreign asset without taking the corresponding exchange rate risk. We applied our method to price a quanto option. Park et al. [62] used a power series expansion method to obtain an analytic approximation value for the quanto option price under the Hull–White stochastic volatility model.

First, we give the quanto option pricing model with Hull–White stochastic volatility, as shown in Park et al. [62]. Let $S(t)$ be a stock price in foreign currency, and $F(t)$ be a foreign exchange (FX) rate, that is the amount of domestic currency value per one foreign currency value. In a risk-neutral world, they are assumed to obey the following stochastic differential equations:

$$
\begin{aligned}
dS(t)/S(t) &= (r_f - \rho_{12}\sigma_1(t)\sigma_2(t))dt + \sigma_1(t)dW_1(t), \\
dF(t)/F(t) &= (r_d - r_f)dt + \sigma_2(t)dW_2(t), \\
d\sigma_1(t)/\sigma_1(t) &= \mu_1 dt + \xi_1 dZ_1(t), \\
d\sigma_2(t)/\sigma_2(t) &= \mu_2 dt + \xi_2 dZ_2(t),
\end{aligned}
$$

where r_d is a risk-free domestic interest rate and r_f is a risk-free foreign interest rate.

The correlations among the Brownian noises are given by $\text{cov}(dW_1(t), dW_2(t)) = \rho_{12}dt$, $\text{cov}(dW_1(t), dZ_1(t)) = \rho_1 dt$, and $\text{cov}(dW_2(t), dZ_2(t)) = \rho_2 dt$. Additionally, $\sigma_1(t)$ and $\sigma_2(t)$ are the stochastic volatilities of the stock price and the FX rate, respectively. This form of the Hull–White stochastic volatility is a little different from that in Table 1 (for more details, please see Park et al. [62]). The parameters μ_1, μ_2, ξ_1, and ξ_2 are constants.

Park et al. [62] considered a specific quanto option with payoff:

$$h^{\text{Quanto}}(\mathbf{S}(T)) = F_0 \max\left(S(T) - K, 0\right), \tag{40}$$

where F_0 is a predetermined FX rate, and K is the strike price. A more general quanto option payoff would be $\max(F_0, F(T)) \max\left(S(T) - K, 0\right)$ (see Jiang et al. [20]). When volatilities $\sigma_1(t)$ and $\sigma_2(t)$ take constant values σ_1 and σ_2, respectively, the authors gave the Black–Scholes quanto option price as:

$$V^{\text{BS-Quanto}}(t, \mathbf{S}) = F_0 e^{-r_d(T-t)} \left(S e^{(r_f - \rho_{12}\sigma_1\sigma_2)(T-t)} N(d_1) - K N(d_2) \right), \tag{41}$$

where

$$\begin{aligned} d_1 &= \frac{\ln \frac{S}{K} + \left(r_f - \rho_{12}\sigma_1\sigma_2 + \frac{1}{2}\sigma_1^2\right)(T-t)}{\sigma_1\sqrt{T-t}}, \\ d_2 &= d_1 - \sigma_1\sqrt{T-t}. \end{aligned}$$

It is easy to obtain the derivative

$$\frac{\partial}{\partial S} V^{\text{BS-Quanto}}(t, \mathbf{S}) = F_0 e^{(r_f - r_d - \rho_{12}\sigma_1\sigma_2)(T-t)} N(d_1).$$

The authors [62] supposed a quanto European call option of the S&P500 index with 1200 strike and a predetermined FX rate of 1100 (KRW/USD). The model parameters shown in Table 8 were observed on 13 October 2010. Furthermore, we assume that the contract multiplier of the S&P500 option is 100 and the maturity is 13 October 2011. Without loss of generality, we set the unobserved values as zeros.

Table 8. Market dataset parameters.

View Date	**13 October 2010**
S&P500	1169.77
FX Rate (KRW/USD)	1127
Volatility of S&P500	18.58%
Volatility of FX Rate	11.83%
Correlation between S&P500 and FX Rate	−0.2297
Correlation between S&P500 and its volatility	−0.55
Volatility of volatility of S&P500	11.72%
Volatility of volatility of FX Rate	16.8%
USD LIBOR(1Y)	0.77%
KRW Treasury Rate(1Y)	2.91%

Notes: FX stands for foreign exchange; KRW stands for South Korean Won; USD stands for US dollar; and LIBOR is London Interbank Offered Rate.

We changed the values of the correlation between the S&P500 and the FX rate and fixed all other parameters. The number of time steps was set to $N = 100$ and the number of simulations was set to $m = 100{,}000$. The numerical results for these models are recorded in Table 9.

Table 9. Quanto option: Numerical results with different correlation coefficients.

ρ_{12}	V_{Appro} (10^6)	V_{MC} (10^6)	Std_{MC} (10^6)	V_{Mar} (10^6)	Std_{Mar} (10^6)	V_{Fun} (10^6)	Std_{Fun} (10^6)	R_1	R_2
−0.6	9.1393	9.1082	0.0462	9.1223	0.0038	9.1162	0.0047	12.1373	9.7825
−0.4	8.8325	8.8187	0.0454	8.8316	0.0037	8.8258	0.0046	12.3813	9.8215
−0.2	8.5311	8.5357	0.0447	8.5473	0.0035	8.5416	0.0045	12.6122	9.8533
0.0	8.2352	8.2592	0.0439	8.2696	0.0034	8.2638	0.0044	12.8264	9.8768
0.2	7.9448	7.9890	0.0432	7.9984	0.0033	7.9924	0.0044	13.0198	9.8906
0.4	7.6599	7.7253	0.0424	7.7335	0.0032	7.7276	0.0043	13.1884	9.8948
0.6	7.3807	7.4679	0.0417	7.4750	0.0031	7.4691	0.0042	13.3285	9.8900

Notes: ρ_{12} is the correlation between S&P500 and FX Rate; and V_{Appro} is the the approximated values calculated by formula in [62].

In Table 9, ρ_{12} stands for the correlation between the S&P500 and FX rate. V_{Appro} is the approximated value obtained by the series expansion method in Park et al. [62]. V_{MC}, V_{Mar}, and V_{Fun} are the estimated values of the MC simulation, the martingale CV method, and the function CV method, respectively. Std_{MC}, Std_{Mar}, and Std_{Fun} are the standard errors of the MC simulation, the martingale CV method, and the function CV method, respectively. $R_1 = Std_{\text{MC}}/Std_{\text{Mar}}$ is the standard error reduction ratio of the martingale CV method compared to the MC simulation, and $R_2 = Std_{\text{MC}}/Std_{\text{Fun}}$ is the the standard error reduction ratio of the function CV method compared to the MC simulation. For the function CV method, the expectation of the corresponding CV can be calculated by using Equation (41) and substituting $\sigma_i\sigma_j$ with $\frac{1}{T}\int_0^T E[\sigma_i(t)]E[\sigma_j(t)]dt$, where $E[Y_i(t)] = Y_i(0)e^{\mu_i t}, i = 1, 2$. It is obvious that our martingale CV method has a larger standard reduction ratio than the function CV method. This, again, shows the efficiency and robustness of our method.

5. Conclusions

In the context of European multi-asset options with stochastic volatilities, we propose a dimension and variance reduction Monte Carlo method. A conditional Monte Carlo pricing formula is deduced, and then the martingale representation theorem is proved. A martingale control variate is combined with the conditional Monte Carlo simulation.

Numerical tests on typical multi-asset options—including exchange options, basket options, and currency options—showed that this method yields considerable variance reduction, not only when compared to a traditional Monte Carlo simulation, but also with respect to the function control variate in Ma and Xu [74].

For future research, it would be interesting and challenging to extend the framework in this paper to price more options with stochastic volatilities, not only European options but also exotic options such as American options or barrier options. Furthermore, it would be interesting to study jump diffusion models with stochastic volatilities. Another important approach is to use this framework in empirical financial studies and risk management. After model parameters are calibrated with real market data, our method can be used to accurately and quickly value option prices which can be widely used in areas of economics and finance. We would also like to extend this method to other areas like risk management and civil engineering.

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Abbreviations

The following abbreviations are used in this manuscript:

MC	Monte Carlo
CV	control variate
CMC	conditional Monte Carlo
FFT	fast Fourier transformation
FX	foreign exchange

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Equity Return Dispersion and Stock Market Volatility: Evidence from Multivariate Linear and Nonlinear Causality Tests

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Abstract: We employ bivariate and multivariate nonlinear causality tests to document causality from equity return dispersion to stock market volatility and excess returns, even after controlling for the state of the economy. Expansionary (contractionary) market states are associated with a low (high) level of equity return dispersion, indicating asymmetries in the relationship between return dispersion and economic conditions. Our findings indicate that both return dispersion and business conditions are valid joint forecasters of stock market volatility and excess returns and that return dispersion possesses incremental information regarding future stock return dynamics beyond that which can be explained by the state of the economy.

Keywords: equity return dispersion; stock market volatility; business cycle; multivariate causality

JEL Codes: C32; E32; G10

1. Introduction

Numerous catalysts, ranging from discount rate factors to cash flow and other related variables, can drive fluctuations in stock markets. While stock market fluctuations do not always signal bad news for investors, monitoring and modelling stock market volatility is crucial, not only for investors in their portfolio management and risk assessment models, but also for policy makers in their assessment of financial fundamentals and investor sentiment. Recent literature has documented that equity return dispersion, measured by the cross-sectional standard deviation of stock returns, either at the individual stock or disaggregate portfolio level, carries reliable information regarding the state of the economy and future stock market volatility [1–3]. In another strand of the literature, however, stock market volatility is linked to economic fundamentals [4,5] and the business cycle [6].

Given the ample evidence on the predictive power of equity return dispersion on stock market volatility and the evidence of causality between stock market volatility and the business cycle, a natural research question is whether the predictive power of return dispersion is driven by a common fundamental factor that drives both stock market volatility and the dispersion of stock returns. To that end, multivariate causality tests provide a valuable avenue for empirical analysis as we are able to test for causality between return dispersion and stock market premium and volatility after controlling for the state of the economy.

This paper contributes to the literature on stock market predictability by exploring the causal relationship between return dispersion and stock market volatility and excess returns via multivariate nonlinear causality tests recently developed by Bai et al. [7–9] and Chow et al. [10]. The advantage of multivariate causality tests, as opposed to bivariate alternatives that are often employed in the literature, is that it allows us to control for business cycles via the business conditions index that we use in our tests and to examine the causality relationship that bivariate alternatives cannot detect. Given the recent evidence by Choudhry et al. [6] of a bidirectional causal relationship between stock market volatility and the business cycle, the multivariate causality tests that control for business cycles in the causal relationship between return dispersion and stock market volatility allow us to explore whether return dispersion possesses any incremental information regarding stock market return dynamics even after controlling for business cycles, and thus enlarges our understanding of the role of return dispersion as an economic state variable. The issue is of interest not only from the perspective of stock market predictability, but it also has significant applicability to the pricing of derivatives, and hedging and portfolio diversification, as volatility forecasts are an integral part of these exercises. On the other hand, bivariate causality tests could detect the causality relationship between any pair of variables that multivariate causality tests cannot detect. Thus, we employ both bivariate and multivariate causality tests in this study.

Performing a combination of linear vs. nonlinear and bivariate vs. multivariate causality tests, we show that linear causality tests generally fail to detect causal effects from return dispersion to excess market returns and volatility. While observing some evidence of causality from return dispersion to both stock market volatility and excess returns, we observe that causality disappears when we control for the business conditions via the Aruoba–Diebold–Scotti business conditions index. Furthermore, we find that the predictive power of business conditions on return dispersion is concentrated on contractionary periods only, suggesting the presence of asymmetric causal interactions between business conditions, equity return dispersion, and stock market volatility.

Both bivariate and multivariate nonlinear causality tests, however, yield significant evidence of causality from return dispersion to both stock market volatility and equity premium. While detecting significant causality from business conditions to return dispersion, we observe that expansionary (contractionary) market states are associated with a low (high) level of equity return dispersion, in line with the findings in Angelidis et al. [2] that high return dispersion is associated with a deterioration of business conditions. Overall, our findings suggest that both return dispersion and business conditions are valid joint forecasters of both the stock market volatility and excess market return and that return dispersion indeed possesses incremental information regarding future stock return dynamics beyond that which can be explained by the state of the economy. The results have significant implications for stock market forecasting models as well as for policy makers to take into account the cross-sectional variation in stock returns and nonlinearities when assessing the predictors of stock market dynamics.

The rest of the paper is organized as follows. Section 2 provides a brief review of the literature on equity return dispersion in asset pricing and investments. Section 3 presents the data and the methodology for linear and nonlinear multivariate causality tests. Section 4 presents the empirical findings and Section 5 concludes the paper.

2. Literature Review

The literature provides ample evidence that associates equity return dispersion with different aspects of risk. In earlier studies focusing on the U.S. stock returns, Christie and Huang [11] and Duffee [12] associated return dispersion with economic expansions and recessions, documenting asymmetries in the cross-sectional dispersion of stock returns with respect to stock market movements and business cycles. Similarly, Loungani et al. [13] found that an index that measures the dispersion among stock prices from different industries has predictive power over unemployment. To that end, early research established evidence of an association between equity return dispersion and macroeconomic indicators.

In other works on return dispersion, studies including those of Stivers [14] and Connolly and Stivers [1] established a link between return dispersion, aggregate market volatility, and idiosyncratic volatility, implying that return dispersion provides signals about future aggregate stock market volatility. Further extending the role of return dispersion to asset pricing models, Stivers and Sun [15] and Bhootra [16] associated the time variation in the value and momentum premia with the variation in the market's cross-sectional return dispersion. Similarly, studies including those of Jiang [17], Demirer and Jategaonkar [18], and Demirer et al. [19] showed that return dispersion serves as a systematic risk factor, carrying a positive price of risk in the cross-section of stock returns, while Demirer and Jategaonkar [18] showed that return dispersion risk is asymmetrically priced, conditional on the market return. In a more recent application to G7 countries, Angelidis et al. [2] further supported the role of return dispersion as an economic state variable and showed that return dispersion reliably predicts the time-variation in stock market returns, volatility, as well as the value and momentum premia observed in the cross-section of stock returns. Similarly, Maio [3] showed that return dispersion consistently forecasts a decline in the excess market returns, with superior out-of-sample performance in predicting the equity premium, compared to alternative predictors, including the dividend yield, term spread, etc.

In another strand of the literature that is related to portfolio management, studies including those of Lillo and Mantegna [20], Solnik and Roulet [21], Baur [22], Statman and Scheid [23,24], and Demirer [25] related return dispersion to the association of asset returns and examined the statistic in the context of portfolio diversification. While Baur [22] noted that return dispersion can be used to obtain additional information about market linkages that is not provided by correlation, Eiling and Gerard [26] used a variant of the dispersion measure in order to examine the time variation in linkages among global stock markets.

Meanwhile, another strand of the literature provides ample evidence linking stock market volatility to real economic activity [4,5] and stock market volatility to future aggregate stock returns [27–30]. In a recent study, applying linear and nonlinear causality tests, Choudhry et al. [6] showed that a bidirectional causal relationship exists between stock market volatility and the business cycle in a sample of four major economies without using return dispersion in their multivariate tests.

Building on the recent evidence from asset pricing tests, Chichernea et al. [31] further supported the role of return dispersion as a systematic risk factor and document that return dispersion has explanatory power for accrual and investment anomalies, associating a high level of return dispersion exposure with conditions that are not conducive to growth and investment. A natural research question, therefore, is what drives the predictive value of return dispersion for future returns and volatility and whether this predictive ability is indeed driven by the information return dispersion possesses regarding the state of the economy. To that end, multivariate causality tests provide an interesting opening as they allow us not only to account for possible nonlinearities in the time series, but also to examine the causal associations between return dispersion and stock market return and volatility after controlling for business conditions.

3. Data and Methodology

3.1. Data

The primary variables of interest in our causality tests are equity return dispersion and stock market volatility, with the Aruoba–Diebold–Scotti business conditions index used as a control variable in our multivariate tests. The sample period covers July 1963 to February 2017, including 13,508 observations of stock and market returns, the Center for Research in Security Prices (CRSP) value-weighted index return, and the one-month Treasury bill rate. From the data, we compute equity return dispersion (RD_t) for day t as the cross-sectional standard deviation of daily stock returns calculated as:

$$RD_t = \sqrt{w_{i,t} \sum_{i=1}^{N} (r_{i,t} - r_{m,t})^2}, \tag{1}$$

where $r_{i,t}$ and $r_{m,t}$ are the return for stock i and the market for day t, respectively; $w_{i,t} = 1/N$ for the equally-weighted cross-sectional dispersion of equity returns; and N is the number of stocks. Following Stivers and Sun [15], Angelidis et al. [2], and Maio [3], we compute the cross-sectional standard deviation of daily returns on 100 portfolios sorted on size and book-to-market ratios, obtained from Ken French's website as an estimate for equity return dispersion. Maio [3] argues that the use of portfolios in the computation of return dispersion mitigates estimation errors due to the presence of illiquid and small stocks in the cross-section of individual stocks. Likewise, we obtain data for daily excess returns on the market, defined as the CRSP value-weighted index return minus the one-month Treasury bill rate, from Ken French's website. Please note that as our study builds on the previous studies regarding the predictive power of return dispersion, in particular Angelidis et al. [2] and Maio [3], we compute return dispersion consistent with these studies. This allows us to compare our findings to previous results and focus on the new insight multivariate tests provide; that is, after controlling for business conditions.

Solnik and Roulet [21] used the market model benchmark to show that return dispersion relates to the cross-sectional correlation of asset returns. However, unlike traditional measures of correlation and volatility, return dispersion provides an aggregate measure of co-movement in a portfolio for a given time period. To that end, the equity return dispersion measure in Equation (1) can be regarded as a measure of directional similarity in stock returns for a given day. In the case of stock market volatility, we follow Choudhry et al. [6] and estimate stock market volatility (SV) by means of the univariate generalized autoregressive conditional heteroskedasticity (GARCH (1,1)) model of CRSP market index returns. Consistent with Choudhry et al. [6], the computation of SV allows us to compare our findings to the previous findings and provide further insight by adding return dispersion to the multivariate tests. It must be noted that we also tried several alternative models, including the exponential GARCH (EGARCH) and Glosten-Jagannathan-Runkle-GARCH (GJR-GARCH) models, to estimate stock market volatility, and the EGARCH model was found to fit the data better than the GARCH and GJR-GARCH models. However, the results using the EGARCH-based estimates of stock market volatility yielded similar findings for the linear and nonlinear causal relationships in both bivariate and multivariate situations (available upon request).

Figure 1 presents the time series plots for daily equity return dispersion (RD) and stock market volatility (SV) during the sample period. Not surprisingly, we observe several notable spikes in both series, particularly during the Asian crisis period in the late 1990s and the global financial crisis periods, in line with the previous studies associating high stock market volatility with recessionary periods and periods of market stress [4,5]. It is interesting that return dispersion values also exhibit similar spikes during these periods. Demirer et al. [32] note that these periods were also associated with spikes observed in the level of global risk aversion, driving equity market correlations higher globally. To that end, the high level of equity return dispersion observed in Figure 1 during periods when stock market volatility also rises suggests that these two series are possibly driven by a common fundamental factor related to the economy.

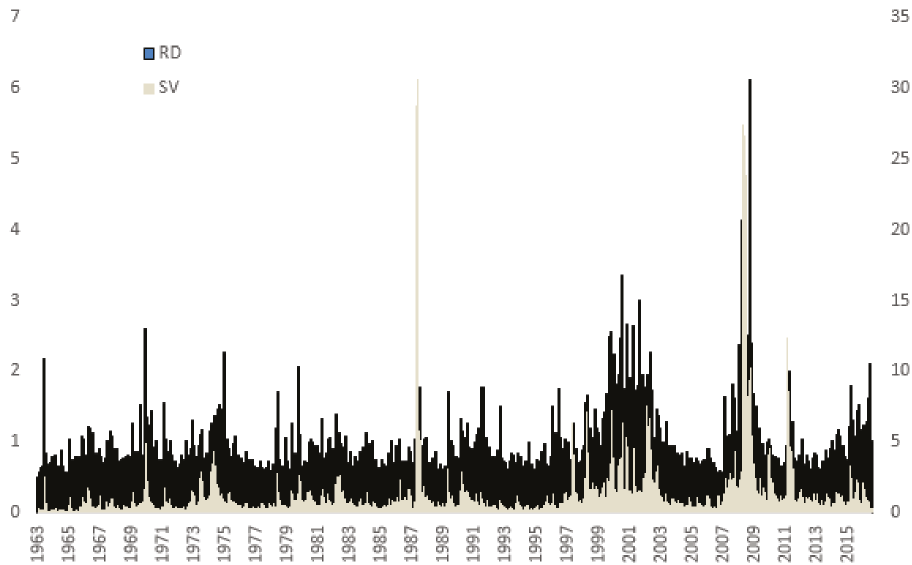

Figure 1. Daily equity return dispersion (RD) and stock market volatility (SV). Note: RD and SV are equity return dispersion and stock market volatility, respectively.

Motivated by studies, including those of Stivers and Sun [15] and Angelidis et al. [2], suggesting that equity return dispersion can predict the time-variation in economic activity, we supplement our multivariate causality tests with the Aruoba–Diebold–Scotti business conditions index (*ADS*) in order to account for economic conditions in the causal effect of return dispersion on stock market return and volatility. The *ADS* index developed in Aruoba et al. [33] measures economic activity at high frequency using a dynamic factor model that includes a number of economic variables. We obtain the data for the *ADS* index from the Philadelphia Fed's website and use this index in our multivariate causality tests in order to track the predictive ability of business conditions along with return dispersion over stock market volatility and premium.

3.2. Methodology

3.2.1. Bivariate Linear Causality Tests

In order to examine the bivariate linear causal relationship between any pair of equity return dispersion (RD_t), stock market volatility (SV_t), equity market premium (MP_t), business conditions index (ADS_t), and the positive (negative) ADS business conditions index values ($ADS1_t$) [($ADS2_t$)], we let x_t and y_t present any pair of RD_t, SV_t, MP_t, ADS_t, $ADS1_t$, and $ADS2_t$ that we are interested in studying and used the widely accepted vector autoregression (VAR) specification and the corresponding Granger causality test [34]. Consider the following two-equation model:

$$x_t = a_1 + \sum_{i=1}^{p} \alpha_i x_{t-i} + \sum_{i=1}^{p} \beta_i y_{t-i} + \varepsilon_{1t}, \tag{2a}$$

$$y_t = a_2 + \sum_{i=1}^{p} \gamma_i x_{t-i} + \sum_{i=1}^{p} \delta_i y_{t-i} + \varepsilon_{2t}, \tag{2b}$$

where x_t and y_t are stationary variables, p is the optimal lag in the system based on the well-known information criteria, such as the Akaike information criterion (AIC), and ε_{1t} and ε_{2t} are the disturbances satisfying the regularity assumptions of the classical linear normal regression model. The variable $\{y_t\}$ is said not to Granger cause $\{x_t\}$ if $\beta_i = 0$ in Equation (2a), for any $i = 1, \ldots, p$. In other words, the past values of $\{y_t\}$ do not provide any additional information on $\{x_t\}$. Similarly, $\{x_t\}$ does not Granger cause $\{y_t\}$ if $\gamma_i = 0$ in Equation (2b), for any $i = 1, \ldots, p$. In order to test for Granger causality, we used the following null hypotheses separately:

$$H_0^1 : \beta_1 = \beta_2 = \cdots = \beta_p = 0, \tag{3a}$$

$$H_0^2 : \gamma_1 = \gamma_2 = \cdots = \gamma_p = 0, \tag{3b}$$

and used the standard *F*-test to empirically test them.

There are four different situations for the causality relationships between RD_t and SV_t in Equations (2a) and (2b): (a) Rejecting H_0^1 but not rejecting H_0^2 implies a unidirectional causality from SV_t to RD_t; (b) rejecting H_0^2 but not rejecting H_0^1 implies a unidirectional causality from RD_t to SV_t; (c) rejecting both H_0^1 and H_0^2 implies the existence of feedback relations; and (d) not rejecting both H_0^1 and H_0^2 implies that RD_t and SV_t are not rejected to be independent. Readers may refer to Bai et al. [7–9], Chow et al. [10], and the references therein for the details of testing H_0^1 and/or H_0^2.

3.2.2. Nonlinearity Tests

In this paper, we first perform a linear causality test and thereafter conduct nonlinear causality tests to test whether there is any linear and nonlinear causality among RD_t, SV_t, MP_t, ADS_t, $ADS1_t$, and $ADS2_t$. If it is necessary to conduct nonlinear causality tests on the variables, we believe that the residuals obtained from performing the linear causality should contain nonlinearity. In addition, RD_t, SV_t, MP_t, ADS_t, $ADS1_t$, and $ADS2_t$ should contain some nonlinear elements so that linear causality cannot eliminate nonlinearity. Thus, in this paper, we conduct a nonlinear test on RD_t, SV_t, MP_t, ADS_t, $ADS1_t$, and $ADS2_t$. We let $\mathrm{Y_t}$ represent RD_t, SV_t, MP_t, ADS_t, $ADS1_t$, and. In order to test for nonlinearity in the variable $\mathrm{Y_t}$, we first remove the linear components in the series $\{\mathrm{Y_t}\}$ using an autoregressive (AR) specification and compute the residuals series of $\{\mathrm{Y_t}\}$ without loss of generality; we also let $\{\mathrm{Y_t}\}$ be the residuals series of $\{\mathrm{Y_t}\}$ if there is no confusion. The series $\{\mathrm{Y_t}\}$ does not possess any nonlinearity if and only if, for any t, the law of corresponding residuals $\{\mathrm{Y_t}\}$ satisfies $\mathrm{L}(\mathrm{Y_t}|\mathrm{Y_{t-1}}) = \mathrm{L}(\mathrm{Y_t})$ and we define $\mathrm{C_1}(\tau) \equiv \mathrm{Pr}(\mathrm{Y_{t-1}} < \tau, \mathrm{Y_t} < \tau)$, $\mathrm{C_2}(\tau) \equiv \mathrm{Pr}(\mathrm{Y_{t-1}} < \tau)$, and $\mathrm{C_3}(\tau) \equiv \mathrm{Pr}(\mathrm{Y_t} < \tau)$. Since $\mathrm{Pr}(\mathrm{Y_t} < \tau|\mathrm{Y_{t-1}} < \tau) = \frac{\mathrm{C_1}(\tau)}{\mathrm{C_2}(\tau)}$, we can test the following hypothesis when testing the existence of the nonlinear of a sequence $\{\mathrm{Y_t}\}$:

$$\mathrm{H_0} : \frac{\mathrm{C_1}(\tau)}{\mathrm{C_2}(\tau)} - \mathrm{C_3}(\tau) = 0, \tag{4}$$

For a residual sequence $\{\mathrm{Y_t}\}$, the dependence test statistic is given by:

$$\mathrm{T_n} = \sqrt{\mathrm{n}}\left(\frac{\mathrm{C_1}(\tau,\mathrm{n})}{\mathrm{C_2}(\tau,\mathrm{n})} - \mathrm{C_3}(\tau,\mathrm{n})\right), \tag{5}$$

where:

$$\mathrm{C_1}(\tau,\mathrm{n}) \equiv \frac{1}{\mathrm{n}}\sum_{\mathrm{t}=2}^{\mathrm{T}} \mathrm{I}_{(\mathrm{y_{t-1}}<\tau)} \cdot \mathrm{I}_{(\mathrm{y_t}<\tau)},$$

$$\mathrm{C_2}(\tau,\mathrm{n}) \equiv \frac{1}{\mathrm{n}}\sum_{\mathrm{t}=2}^{\mathrm{T}} \mathrm{I}_{(\mathrm{y_{t-1}}<\tau)},$$

$$\mathrm{C_1}(\tau,\mathrm{n}) \equiv \frac{1}{\mathrm{n}}\sum_{\mathrm{t}=2}^{\mathrm{T}} \mathrm{I}_{(\mathrm{y_t}<\tau)},$$

$n = T - 1$, and T is the length of residual $\{Y_t\}$. Under this condition, if the residual $\{Y_t\}$ is iid, then the test statistic $T_n \to N(0, \sigma^2(\tau))$, as n is large enough and the hypothesis: $H_0 : \frac{C_1(\tau)}{C_2(\tau)} - C_3(\tau) = 0$ is rejected at level α if $|T_n|/\hat{\sigma}^2(\tau) > z_{\frac{\alpha}{2}}$. In this situation, the series $\{Y_t\}$ possesses any nonlinearity. We note that the nonlinear test takes GARCH effects into consideration in the test (Hui et al. [35] and Bai et al. [9]).

3.2.3. Multivariate Granger Causality tests

In this section, we review the theory of both linear and nonlinear causality and discuss how to apply the linear and nonlinear Granger causality tests to identify the causality relationships among RD_t, ADS_t, $ADS1_t$, and $ADS2_t$ to SV_t and MP_t. To test the linear and nonlinear causality relationship between a vector of stationary variables from RD_t, ADS_t, $ADS1_t$, and $ADS2_t$ and another vector of stationary variable of either SV_t and MP_t, we let $x_t = (x_{1,t}, \ldots, x_{n_1,t})'$ and $y_t = (y_{1,t}, \ldots, y_{n_2,t})\prime$ with $n_1 = 2$ and $n_2 = 1$, $x_{1,t} = RD_t$, $x_{2,t} = ADS_t$, $ADS1_t$, or $ADS2_t$, $x_{1,t} = SV_t$ or MP_t, and $n_1 + n_2 = n$ series in total.

Multivariate Linear Causality

To test the linear causality relationship between a vector of stationary variables from $x_t = (x_{1,t}, \ldots, x_{n_1,t})'$ and $y_t = (y_{1,t}, \ldots, y_{n_2,t})\prime$, one could construct the following $n-$ VAR equations:

$$\begin{pmatrix} x_t \\ y_t \end{pmatrix} = \begin{pmatrix} A_{x[n_1\times 1]} \\ A_{y[n_2\times 1]} \end{pmatrix} + \begin{pmatrix} A_{xx}(L)_{[n_1\times n_1]} & A_{xy}(L)_{[n_1\times n_2]} \\ A_{yx}(L)_{[n_2\times n_1]} & A_{yy}(L)_{[n_2\times n_2]} \end{pmatrix}\begin{pmatrix} x_{t-1} \\ y_{t-1} \end{pmatrix} + \begin{pmatrix} e_{x,t} \\ e_{y,t} \end{pmatrix}, \tag{6}$$

where $A_{x[n_1\times 1]}$ and $A_{y[n_2\times 1]}$ are two vectors of intercept terms, and $A_{xx}(L)_{[n_1\times n_1]}$, $A_{yx}(L)_{[n_2\times n_1]}$, $A_{xy}(L)_{[n_1\times n_2]}$, and $A_{yy}(L)_{[n_2\times n_2]}$ are matrices of lag polynomials.

In order to test the following null hypotheses separately:

(1) $H_0^1 : A_{xy}(L) = 0$,
(2) $H_0^2 : A_{yx}(L) = 0$, and,
(3) both $H_0^1 : A_{xy}(L) = 0$ and $H_0^2 : A_{yx}(L) = 0$,

We should obtain the residual covariance matrix Σ from the full model using an ordinary least squares estimation (OLSE) for each equation without imposing any restriction on the parameters, compute the residual covariance matrix Σ_0 from the restricted model in Equation (6) using OLSE for each equation with the restriction on the parameters imposed by the null hypothesis H_0^1, H_0^2 or both H_0^1 and H_0^2, and obtain the following statistic:

$$(T - c)(\log|\Sigma_0| - \log|\Sigma|) \tag{7}$$

where T is the number of usable observations, c is the number of parameters estimated in each equation of the unrestricted system, and $\log|\Sigma_0|$ and $\log|\Sigma|$ are the natural logarithms of the determinants of restricted and unrestricted residual covariance matrices, respectively. When the null hypothesis is true, this test statistic has an asymptotic χ^2 distribution with the degree of freedom equal to the number of restrictions on the coefficients in the system.

Multivariate Nonlinear Causality

After applying the VAR model to identify the linear causality relationships from RD_t, ADS_t, $ADS1_t$, and $ADS2_t$ to SV_t and MP_t, we obtain their corresponding residuals $\{\hat{\varepsilon}_{1t}\}$ and $\{\hat{\varepsilon}_{2t}\}$ to test the nonlinear causality with the residual series. For simplicity, in this section, we denote $X_t = (X_{1,t}, \ldots, X_{n_1,t})\prime$ and $Y_t = (Y_{1,t}, \ldots, Y_{n_2,t})'$ to be the corresponding residuals of any two vectors of variables to be examined. We define the lead vector and lag vector of a time series, say $X_{i,t}$, as follows: for $X_{i,t}$, $i = 1, \ldots, n$, the m_{x_i}-length lead vector, and the L_{x_i}-length lag vector of $X_{i,t}$ to be:

$$X_{i,t}^{m_{x_i}} \equiv \left(X_{i,t}, X_{i,t+1}, \ldots, X_{i,t+m_{x_i}-1}\right), m_{x_i} = 1, 2, \ldots, t = 1,\ 2,\ \ldots,$$

$$X_{i,t-L_{x_i}}^{L_{x_i}} \equiv \left(X_{i,t-L_{x_i}}, X_{i,t-L_{x_i}+1}, \ldots, X_{i,t-1}\right), L_{x_i} = 1,\ 2,\ \ldots,\ t = L_{x_i}+1, L_{x_i}+2, \ldots, \text{respectively.}$$

We denote $M_x = \left(m_{x1}, \ldots, m_{x_{n_1}}\right)$, $L_x = \left(L_{x1}, \ldots, L_{x_{n_1}}\right)$, $m_x = \max(m_{x1}, \ldots, m_{n_1})$, and $l_x = \max\left(L_{x1}, \ldots, L_{x_{n_1}}\right)$. The m_{y_i}-length lead vector, $Y_{i,t}^{m_{y_i}}$, the L_{y_i}-length lag vector, $Y_{i,t-L_{y_i}}^{L_{y_i}}$, of $Y_{i,t}$, and M_y, L_y, m_y, and l_y can be defined similarly.

To test the null hypothesis, H_0, that Y_t does not strictly Granger cause $X_t = (X_{1,t}, \ldots, X_{n_1,t})\prime$ under the assumptions that the time series vector variables $X_t = (X_{1,t}, \ldots, X_{n_1,t})\prime$ and $Y_t = (Y_{1,t},\ \ldots, Y_{n_2,t})'$ are strictly stationary, weakly dependent, and satisfy the mixing conditions stated in Denker and Keller [36], we first defined the following four events given that m_x, m_y, L_x, L_y, and $e > 0$:

$$\left\{\|X_t^{M_x} - X_s^{M_x}\| < e\right\} \equiv \left\{\|X_{i,t}^{M_{x_i}} - X_{i,s}^{m_{x_i}}\| < e, \text{ for any } i = 1, \ldots, n_1\right\};$$

$$\left\{\|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\| < e\right\} \equiv \left\{\|X_{i,t-L_{x_i}}^{L_{x_i}} - X_{i,s-L_{x_i}}^{L_{x_i}}\| < e, \text{ for any } i = 1, \ldots, n_1\right\};$$

$$\left\{\|Y_t^{M_y} - Y_s^{M_y}\| < e\right\} \equiv \left\{\|Y_{i,t}^{m_{y_i}} - Y_{i,s}^{m_{y_i}}\| < e, \text{ for any } i = 1, \ldots, n_2\right\}; \text{ and}$$

$$\left\{\|Y_{t-L_y}^{L_y} - Y_{s-L_y}^{L_y}\| < e\right\} \equiv \left\{\|Y_{i,t-L_{y_i}}^{L_{y_i}} - Y_{i,s-L_{y_i}}^{L_{y_i}}\| < e, \text{ for any } i = 1, \ldots, n_2\right\};$$

where $\|\cdot\|$ denotes the maximum norm which is defined as $\|X - Y\| = \max(|x_1 - y_1|, |x_2 - y_2|, \ldots, |x_n - y_n|)$ for any two vectors $X = (x_1, \ldots, x_n)$ and $Y = (y_1, \ldots, y_n)$. The vector series $\{Y_t\}$ is said not to strictly Granger cause another vector series $\{X_t\}$ if:

$$\begin{aligned} &\Pr\left(\| X_t^{M_x} - X_s^{M_x}\| < e \middle| \|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\| < e, \|Y_{t-L_y}^{L_y} - Y_{s-L_y}^{L_y}\| < e, \right) \\ &= \Pr\left(\| X_t^{M_x} - X_s^{M_x}\| < e \middle| \|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\| < e\right) \end{aligned} \tag{8}$$

where $Pr(\cdot|\cdot)$ denotes conditional probability.

If the null hypothesis, H_0, is true, the test statistic:

$$\sqrt{n}\left(\frac{C_1(M_x + L_x, L_y, e, n)}{C_2(L_x, L_y, e, n)} - \frac{C_3(M_x + L_x, e, n)}{C_4(L_x, e, n)}\right), \tag{9}$$

is distributed as $N\left(0, \sigma^2(M_x, L_x, L_y, e)\right)$. When the test statistic is too far away from zero, we reject the null hypothesis. Readers may refer to Bai et al. [7–9] and Chow et al. [10] for the definitions of C_1, C_2, C_3, and C_4, and more information on the estimates of Equation (9).

4. Empirical Results

Although not reported due to space considerations, the summary statistics reveal evidence of non-normality, indicated by highly significant Jarque–Bera statistics, with all four-time series (i.e., RD_t, SV_t, ADS_t and equity market premium, MP_t) exhibiting significant kurtosis. We also observe significant skewness for both RD_t and SV_t, suggesting greater likelihood of experiencing large values for these variables. Finally, in unreported findings, unit root tests based on the augmented Dickey and Fuller [37] show that the series are stationary.

4.1. Descriptive Statistics and Stationarity Test

Before describing the nonlinear causality tests, we first report in Table 1 the basic descriptive statistics and the most commonly used stationarity test, the augmented Dickey–Fuller test, for all the variables RD_t, ADS_t, SV_t and MP_t, examined in our paper. From the table, we find that the means of all the variables are significantly positive at the 1 percent level except ADS_t that is significantly negative at the 1 percent level. The skewness estimates show that RD_t and SV_t are positively skewed while ADS_t and MP_t are negatively skewed. Among them, RD_t, ADS_t, and MP_t are significant at the 1 percent, while the skewness of SV_t is not significant. We also find that all variables have positive excess kurtosis at the 1 percent level. Furthermore, from the skewness, kurtosis, and Jarque–Bera (J–B) test statistics, we conclude that the variables are obviously not normally distributed. The results of the augmented Dickey–Fuller test exhibited in Table 1 do not reject that all variables are strictly stationary. Thus, on the premise of the strictly stationary series, we proceed with the causality analysis.

Table 1. Descriptive statistics and the augmented Dickey–Fuller (ADF) test.

	Mean	Stdev	Skewness	Kurtosis	J-B	ADF Test
RD_t	0.627 ***	0.275	4.057 ***	35.136 ***	732,071.353 ***	−8.9165 ***
SV_t	1.000 ***	1.778	8.723	101.069 ***	5,921,984.155 ***	−9.4998 ***
MP_t	0.025 ***	0.988	−0.508 ***	15.633 ***	138,157.710 ***	−82.3209 ***
ADS_t	−0.018 ***	0.876	−1.206 ***	3.921 ***	11,929.823 ***	−7.7651 ***

Note: RD_t, SV_t, MP_t, and ADS_t refer to equity return dispersion, stock market volatility, equity market premium, and business conditions index, respectively. This table reports the summary statistics including the mean, standard deviation (s.d.), skewness, excess kurtosis, Jarque–Bera (JB) test, and the augmented Dickey–Fuller test. The symbols *, **, and *** denote the significance at the 10%, 5%, and 1% levels, respectively.

4.2. Bivariate Causality Tests

We begin our discussion by presenting the findings from bivariate causality tests. Table 2 presents the findings for the bivariate linear Granger causality tests. The optimal lag length for each case based on the well-known information criteria, such as Bayesian Information Criterion (BIC) and Akaike Information Criterion(AIC), are also presented along with the test statistics. Examining the findings in Panel A, we observe significant causality from equity return dispersion to both the stock market volatility and equity market premium, consistent with the evidence in Angelidis et al. [2]. Interestingly, however, we see that the causality from return dispersion becomes insignificant after controlling for business conditions measured by the ADS_t index. Following the suggestion by Angelidis et al. [2] that a relatively high return dispersion predicts a deterioration in business conditions, we distinguished between good and bad business conditions and created two additional variables $ADS1_t$ ($ADS2_t$) representing the positive (negative) ADS_t business conditions index values, respectively. However, we see in Panel A that differentiating between good and bad business conditions still yields insignificant causal effects from return dispersion, suggesting that business conditions serve as the primary driver of stock market volatility, rendering the predictive power of return dispersion insignificant.

The findings in Panel B further support these observations, suggesting that business conditions have significant predictive power over both stock market volatility and equity return dispersion. However, interestingly, the predictive power of business conditions is concentrated on contractionary periods only, suggesting asymmetric causal interactions between business conditions, equity return dispersion and stock market volatility. Overall, the findings in Table 2 show that the level of economic activity plays a significant role in studying linear causality from return dispersion to both stock market volatility and equity market premium.

Table 2. Bivariate linear causality tests.

Panel A: The Predictive Power of Equity Return Dispersion				
	$RD_t \rightarrow SV_t$	$RD_t \rightarrow MP_t$	$RD_t \rightarrow SV_t \mid ADS_t$	$RD_t \rightarrow MP_t \mid ADS_t$
Lags	15	9	16	16
F-Stat	188.760 ***	3.196 ***	9.716×10^{-7}	1.136×10^{-8}
	$RD_t \rightarrow SV_t \mid ADS1_t$	$RD_t \rightarrow SV_t \mid ADS2_t$	$RD_t \rightarrow MP_t \mid ADS1_t$	$RD_t \rightarrow MP_t \mid ADS2_t$
Lags	9	9	9	9
F-Stat	1.729×10^{-6}	1.714×10^{-6}	1.744×10^{-8}	1.749×10^{-8}
Panel B: The Predictive Power of Business Conditions				
	$ADS1_t \rightarrow SV_t$	$ADS2_t \rightarrow SV_t$	$ADS1_t \rightarrow MP_t$	$ADS2_t \rightarrow MP_t$
Lags	16	16	9	9
F-Stat	1.146	3.579 ***	0.738	1.768
	$ADS_t \rightarrow RD_t$	$ADS1_t \rightarrow RD_t$	$ADS2_t \rightarrow RD_t$	
Lags	9	9	9	
F-Stat	4.068 ***	0.513	5.967 ***	

Note: RD_t, SV_t, MP_t and ADS_t refer to equity return dispersion, stock market volatility, equity market premium, and business conditions index, respectively. $ADS1_t$ ($ADS2_t$) represents the positive (negative) business conditions index values, respectively. The notation "$\rightarrow$" indicates causality and "$RD_t \rightarrow SV_t \mid ADS_t$" indicates causality from RD_t to SV_t after controlling for ADS_t. *, **, *** indicate significance at 5, 1, and 0.1 percent level, respectively.

Table 3 presents the results from the nonlinearity tests based on Hui et al. [35] presented in Section 3.2.2. The tests indicate significant evidence of nonlinearity in all-time series at the highest significance level, justifying the use of subsequent nonlinear causality tests. Table 4 presents the results from bivariate nonlinear causality tests. Examining the results in Panels A and B, we observe a significant linear causal relationship from return dispersion to both stock market volatility and equity market premium even after including the ADS_t business conditions index. Furthermore, we observe in Panel C that there exists significant causality from business conditions to return dispersion, but with some degree of asymmetry such that expansionary (contractionary) market states are associated with a low (high) level of equity return dispersion, indicating a higher (lower) degree of directional similarity in stock returns, respectively. To that end, the findings from bivariate tests clearly indicate that the predictive power of equity return dispersion over stock market volatility and equity premium is largely asymmetric with regime specific patterns. This finding is indeed significant for not only stock market forecasting models, but also in the pricing of stock options, as volatility forecasts are crucial in pricing derivatives as well as the estimation of optimal hedge ratios.

Table 3. Nonlinearity Tests.

	ADS_t	$ADS1_t$	$ADS2_t$	RD_t	SV_t	MP_t
Lags	11	10	16	10	15	2
T-Stat	7.734 ***	7.845 ***	7.893 ***	8.970 ***	3.574 ***	8.547 ***

Note: RD_t, SV_t, MP_t and ADS_t refer to equity return dispersion, stock market volatility, equity market premium, and business conditions index, respectively. $ADS1_t$ ($ADS2_t$) represents the positive (negative) business conditions index, respectively; *** indicate significance at 0.1 percent level.

Table 4. Bivariate nonlinear causality tests.

Panel A: The Predictability of Stock Market Volatility				
Lags	$RD_t \rightarrow SV_t$	$RD_t \rightarrow SV_t \mid ADS_t$	$RD_t \rightarrow SV_t \mid ADS1_t$	$RD_t \rightarrow SV_t \mid ADS2_t$
1	7.879 ***	7.8190 ***	7.758 ***	7.824 ***
2	7.718 ***	7.665 ***	7.533 ***	7.525 ***
3	7.637 ***	7.659 ***	7.533 ***	7.621 ***
4	7.908 ***	7.871 ***	7.745 ***	7.772 ***
5	7.461 ***	7.484 ***	7.309 ***	7.449 ***
6	7.155 ***	7.207 ***	7.141 ***	7.279 ***
7	6.770 ***	6.813 ***	6.611 ***	6.662 ***
8	6.617 ***	6.721 ***	6.461 ***	6.535 ***
9	5.984 ***	6.169 ***	5.741 ***	5.884 ***
10	5.918 ***	6.067 ***	5.646 ***	5.742 ***
Panel B: The Predictability of Equity Market Premium				
Lags	$RD_t \rightarrow MP_t$	$RD_t \rightarrow MP_t \mid ADS_t$	$RD_t \rightarrow MP_t \mid ADS1_t$	$RD_t \rightarrow MP_t \mid ADS2_t$
1	11.365 ***	11.379 ***	11.363 ***	11.302 ***
2	12.910 ***	13.079 ***	12.904 ***	12.877 ***
3	12.878 ***	13.053 ***	12.867 ***	12.928 ***
4	13.357 ***	13.643 ***	13.364 ***	13.428 ***
5	13.275 ***	13.693 ***	13.272 ***	13.420 ***
6	12.519 ***	12.931 ***	12.527 ***	12.694 ***
7	11.823 ***	12.206 ***	11.844 ***	12.038 ***
8	11.805 ***	12.155 ***	11.807 ***	12.048 ***
9	11.716 ***	11.996 ***	11.695 ***	11.950 ***
10	11.104 ***	11.405 ***	11.068 ***	11.321 ***
Panel C: The Predictive Power of Business Conditions				
Lags	$ADS_t \rightarrow RD_t$	$ADS1_t \rightarrow RD_t$	$ADS2_t \rightarrow RD_t$	
1	−1.122	−5.676 ***	1.755 *	
2	−1.366	−6.626 ***	1.808 *	
3	−1.352	−6.930 ***	2.627 **	
4	−2.015 *	−6.917 ***	2.317 *	
5	−0.820	−4.650 ***	2.711 **	
6	−1.718 *	−5.231 ***	2.311 *	
7	−2.147 *	−5.412 ***	2.425 **	
8	−2.148 *	−4.913 ***	1.708 *	
9	−1.919 *	−4.669 ***	1.928 *	
10	−1.987 *	−4.427 ***	1.053	

Note: RD_t, SV_t, MP_t and ADS_t refer to equity return dispersion, stock market volatility, equity market premium, and business conditions index, respectively. The notation "→" indicates causality and "$RD_t \rightarrow SV_t \mid ADS_t$" indicates causality from RD_t to SV after controlling for ADS_t. *, **, *** indicate significance at 5, 1, and 0.1 percent level, respectively.

4.3. Multivariate Granger Causality Tests

Having established evidence suggesting that the level of economic activity plays a significant role in studying causality from return dispersion to both stock market volatility and equity market premium, we now proceed with the multivariate causality tests. Table 5 presents the findings for the multivariate linear Granger causality tests explained in Section 3.2.3. We observe in Panel A that multivariate linear Granger causality exists from the return dispersion and business conditions to stock market volatility at the highest significance level, while the same does not hold for equity market premium, regardless of the distinction between expansionary or contractionary business conditions.

Table 5. Multivariate linear causality tests.

	Panel A: The Predictability of Stock Market Volatility		
	RD_t+ADS_t→SV_t	RD_t+$ADS1_t$→SV_t	RD_t+$ADS2_t$→SV_t
Lags	10	9	9
LR	535.909 ***	560.136 ***	573.599 ***
	Panel B: The Predictability of Equity Market Premium		
	RD_t+ADS_t→MP_t	RD_t+$ADS1_t$→MP_t	RD_t+$ADS2_t$→MP_t
Lags	10	9	9
LR	37.812	37.456	39.096

Note: RD_t, SV_t, MP_t and ADS_t refer to equity return dispersion, stock market volatility, equity market premium, and business conditions index, respectively. $ADS1_t$($ADS2_t$) represents the positive (negative) business conditions index values, respectively. The notation "RD_t+ADS_t→X" indicates RD_t and ADS_t together predict variable X. *, **, *** indicate significance at 5, 1, and 0.1 percent level, respectively.

On the other hand, similar to the findings observed for the bivariate case, when we examine the findings from the multivariate nonlinear tests, presented in Table 6, we observe that equity return dispersion and business conditions together have significant predictive power over both the stock market volatility and equity market premium at the highest statistical significance level. The predictive power of RD_t and ADS_t together is robust regardless of the state of economic activity, implied by significant findings for both $ADS1_t$ and $ADS2_t$. To that end, our findings underline the significance of nonlinearity in the causal relationship between return dispersion and stock market premium and volatility but also suggest that equity return dispersion along with a measure of economic conditions can be used to improve forecasting models for both return and volatility of stock market returns.

Table 6. Multivariate nonlinear causality tests.

	Panel A: The Predictability of Stock Market Volatility		
Lags	RD_t+ADS_t→SV_t	RD_t+$ADS1_t$→SV_t	RD_t+$ADS2_t$→SV_t
1	7.706 ***	7.661 ***	7.614 ***
2	7.529 ***	7.454 ***	7.217 ***
3	7.140 ***	7.286 ***	7.037 ***
4	6.736 ***	7.496 ***	6.565 ***
5	6.321 ***	6.954 ***	5.967 ***
6	5.818 ***	6.610 ***	5.694 ***
7	5.380 ***	6.107 ***	4.963 ***
8	5.447 ***	6.016 ***	4.969 ***
9	4.731 ***	5.387 ***	4.095 ***
10	4.665 ***	5.168 ***	4.108 ***
	Panel B: The Predictability of Equity Market Premium		
Lags	RD_t+ADS_t→MP_t	RD_t+$ADS1_t$→MP_t	RD_t+$ADS2_t$→MP_t
1	11.271 ***	11.296 ***	11.260 ***
2	12.523 ***	12.655 ***	12.280 ***
3	12.557 ***	12.594 ***	12.370 ***
4	13.092 ***	12.988 ***	12.846 ***
5	12.590 ***	12.727 ***	11.980 ***
6	11.753 ***	11.797 ***	11.288 ***
7	10.6764 ***	10.733 ***	10.478 ***
8	10.749 ***	10.493 ***	10.584 ***
9	10.662 ***	10.577 ***	10.141 ***
10	10.075 ***	9.923 ***	9.601 ***

Note: RD_t, SV_t, MP_t and ADS_t refer to equity return dispersion, stock market volatility, equity market premium, and business conditions index, respectively. $ADS1_t$ ($ADS2_t$) represents the positive (negative) business conditions index values, respectively. The notation "RD_t+ADS_t→X" indicates RD_t and ADS_t together predict variable X. *, **, *** indicate significance at 5, 1, and 0.1 percent level, respectively.

Angelidis et al. [2] showed that a relatively high return dispersion predicts a deterioration in business conditions, establishing a link between return dispersion and the business cycle. Therefore, one might be tempted to conclude that the predictive power of return dispersion over stock market volatility is, in fact, driven by its predictive power over the business cycle, which, in turn, is shown to have predictive power over stock market volatility (Choudhry et al. [6]). To this end, multivariate tests allow us to check the robustness of the predictive power of return dispersion by controlling for business conditions in our tests. Therefore, the evidence of causality from return dispersion to stock market volatility even after controlling for business conditions suggests that return dispersion conveys incremental information over stock market volatility beyond which is captured by business conditions. In this sense, it supports the previous findings in Demirer and Jategaonkar [18] and others that return dispersion is more likely to capture shocks related to fundamental economic restructuring, rather than the business cycle. Overall, multivariate tests add new insight that one cannot capture via bivariate counterparts, suggesting that return dispersion possesses incremental predictive content over stock market volatility that business conditions alone cannot capture, and this is an important consideration to improve the accuracy of volatility forecasting models.

5. Conclusions

This paper contributes to the literature on stock market predictability by exploring the causal relationships between equity return dispersion, stock market volatility, and excess returns via multivariate nonlinear causality tests recently developed by Bai et al. [7–9]. Performing a combination of linear vs. nonlinear and bivariate vs. multivariate causality tests, we show that linear causality tests generally fail to detect causal effects from return dispersion to excess market returns and volatility. Both bivariate and multivariate nonlinear causality tests, however, yield significant evidence of causality from return dispersion to both stock market volatility and equity premium, even after controlling for the state of the economy. Overall, our findings suggest that both return dispersion and business conditions are valid joint forecasters of both the stock market volatility and excess market return and that return dispersion indeed possesses incremental information regarding future stock return dynamics beyond which can be explained by the state of the economy.

The findings have significant practical implications for the forecasting of stock market volatility dynamics with a possible extension to forecasting risk premia along the lines of Stivers and Sun [15]. As Angelidis et al. [2] note, return dispersion provides a timely and model free estimation of risk. Considering our finding that return dispersion captures incremental information about stock market volatility beyond which can be captured by the level of economic activity, one can use this model-free statistic to improve volatility forecasting models; however, that can only be achieved using nonlinear specifications, as our findings imply. Similarly, the fact that return dispersion offers a timely estimate of risk also allows one to update volatility forecasts in a timely and relatively model-free framework. Furthermore, given the integrated nature of global markets, one can also use return dispersion measures across markets in order to use cross-market dispersion information to improve volatility forecasts in a multi-market setting. This could also lead the path to improved models of co-movement in which return dispersion is used across multiple markets.

There are many directions in which our paper can be extended. One possible extension could include forecasting stock market volatility from equity return dispersion. Future studies could also apply the Copulas approach or other approaches to examine the relationship between equity return dispersion and stock market volatility. So far, to the best of our knowledge, there is no theory explaining whether it is equity return dispersion that causes stock market volatility or it is stock market volatility that causes equity return dispersion or other variables that cause both equity return dispersion and stock market volatility. Thus, another interesting extension is to develop an economic theory to explain the causality between equity return dispersion and stock market volatility. One possible explanation is that it is due to investors' conservative and representative heuristics that relate to the causality of both equity return dispersion and stock market volatility; see, for example, Lam et al. [38,39], Fung et al. [40], Guo et al. [41], and the references therein for more information.

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Information Disclosure Ranking, Industry Production Market Competition, and Mispricing: An Empirical Analysis

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Abstract: Improving the transparency of corporate information disclosure is a key principle of corporate governance in Taiwan. This study uses the information disclosure assessment system established by the information disclosure and transparency ranking system to explore whether information transparency can reduce the degree of mispricing. The study uses the data of 10,686 listed companies in Taiwan for the period from 2005 to 2014. We find that a higher information disclosure ranking (IDR) of rated companies corresponds to a more substantial reduction in the degree of mispricing. Moreover, we discover that product market competition affects mispricing in that smaller degrees of mispricing reflect greater exclusivity; this suggests that lower industry transaction and competition costs lead to less substantial mispricing. Finally, we observe that the effect of information disclosure score on the degree of mispricing is lower in more exclusive industries. Furthermore, a regression process using instrumental variables reveals that IDRs have the significant effect of reducing the degree of mispricing.

Keywords: information disclosure ranking; industry production market competition; mispricing; Taiwan stock market

JEL Classification: G18; G30; G34

1. Introduction

Financial fraud, such as that committed by Tyco, Enron, and WorldCom, has become prevalent. Some internal managers or shareholders take advantage of their own business operations out of self-interest, leaving investors with insufficient information in a relatively weak position. Detecting fraud that causes loss to investors and corporate decline is difficult [1–3].

Therefore, in addition to a greater amount of attention paid by scholars and people practicing business to the matter of information disclosure, financial supervision agencies in various countries have developed guidelines for measuring transparency when encouraging enterprises to improve information disclosure. In 2003, the Taiwan Stock Exchange Corporation (TSEC) entrusted the Securities and Futures Institute (SFI) with the task of improving the information disclosure system to ensure a reduction in information asymmetry between insiders and outsiders on all companies listed in the TSEC. The purpose of this information disclosure system is to plan and design evaluation indicators that meet the needs of the information disclosure and transparency ranking system (IDTRS).

The investment publication is expected to be capable of easily determining the degree of corporate information asymmetry by publishing evaluation grades for listed companies annually.

Differences in information disclosure often imply that various agency problems [4,5], stock liquidity [6,7], corporate capital costs [8,9], and earnings quality [10] may influence enterprise value. Moreover, the evaluation level naturally becomes an auxiliary reference for investor decisions.

The relationship between information disclosure quality and corporate value is inextricable. Improving the integrity of information disclosure can improve the quality of information disclosure, reduce corporate capital costs, and increase shareholder wealth [11]. This effectively repairs damage caused by information asymmetry between shareholders and operators [12,13]; moreover, it can mitigate the effect of excessive executive compensation on company value and enhance corporate value [14]. Merton [15] indicated that the complete disclosure of information helps investors identify with the company and attract new investors, which can reduce the cost of capital and increase the value of the company. Diamond and Verrecchia [7] also discovered that incensement in response to information disclosure can reduce information asymmetry and transaction costs, improve liquidity, and reduce corporate capital costs [16–18]. Klapper and Love [19] explored 14 emerging markets and discovered that more effective corporate governance corresponds to favorable operational performance and corporate value. Bai et al. [20], Black et al. [21], and Braga-Alves and Shastri [22] have examined corporate governance in China, the Soviet Union, Mexico, and Brazil, respectively, and its relationship with company value, and they have reached the same conclusion as the aforementioned study. Ho et al. [23] applied the data of listed companies in Taiwan for the period from 2005 to 2013 to demonstrate that product market competition is negatively correlated with corporate value and that when product market competition is weak, information disclosure is more conducive to company value.

According to the aforementioned research, information disclosure can effectively reduce information asymmetry, reduce company costs, and enhance company value. However, because information disclosure also has external costs, more disclosure is not always better. Excessive disclosure of information may provide competitors with a better understanding of the company's strategy, profitability, and innovation level as well as weaken competitive advantages [24]. Bloomfield and Fischer [25] explored the effects of information disclosure on capital costs, reporting that corporate capital costs increase when firms believe that investors respond to noncritical disclosures.

Product market competition is often considered an external mechanism that affects information disclosure [23]. Information disclosure is endogenous but also influenced by the market competition environment. One view holds that industries with low levels of competition tend to have excess returns and therefore low levels of information disclosure. Information disclosure can also help sellers to distinguish themselves from competitors. However, the fierce competition in the product market is not always beneficial. Other studies have conducted a relatively comprehensive exploration of market competition level by measuring the degree of market product differentiation; they have discovered that higher levels of competition correspond to lower likelihood of high-quality information disclosure. Research has also demonstrated that if the cost of disclosure is high, companies will disclose higher-quality information. When the market itself is more competitive and disclosure cost is higher, competitors will tend to disclose higher-quality information to mitigate high costs. When the degree of competition in the market is not high, competition will always lead to the disclosure of low-quality information regardless of the level of cost.

The degree of mispricing affects the choice of financing method. Baker et al. [26] indicated that when companies rely heavily on equity financing, the effect of mispricing on equity financing is more obvious. However, even if external financing is not required, mispricing may directly affect company investments. The degree of mispricing is affected by many factors [27]. Sloan [28] proposed that investors do not understand that inherent future earnings information is the primary cause of mispricing. Moreover, because the quality of public information remains at the same level, an increased amount of information does not necessarily correspond to a reasonable equity valuation. Compliance with regulations improves company information environments, reduces mispricing, and increases stock market efficiency. Furthermore, policymakers should consider the quality of information provided when attempting to increase capital market efficiency by forcing more disclosures.

Emerging markets possess the characteristics of rapid economic development and remarkable market potential. However, their market economic system remains in a stage of gradual improvement, their external supervision mechanism is not perfect, their information disclosure mechanism is incomplete, and their internal control system of listed companies is inadequate. Investors are more likely to be in an unfavorable position when investing with limited information acquisition and professional knowledge. Therefore, improving the level of investor protection and exploring the relationship between information disclosure and degree of corporate value is necessary to enable investors to more accurately judge investment value. Some scholars have turned their attention away from mature markets to investigate whether emerging markets are subject to the same phenomenon [29].

Investor relations indicators provided by the Association for Investment Management and Research (AIMR) and the Center for International Financial Analysis and Research (CIFAR) can be used as a measure of information disclosure, in addition to other variables used as information disclosure agents [30,31]. However, the AIMR score is not available after 1996, and the CIFAR indicator system does not include Taiwan. We use the SFI information disclosure ranking (IDR) as a measure of information disclosure quality and expand the scope of application of SFI IDRs. By contrast, SFI forms a research team composed of experts from independent parties—consisting of the accounting and finance profession, academic researchers, in-house research staff, and IT personnel—using 114 measures to evaluate the information quality of all listed firms, except for some firms with inadequate data or under regulatory investigation. Therefore, the disclosure scores are based on the same set of information criteria and are not skewed to large firms and variation in accounting standards. The research results are highly relevant to Taiwan's actual situation and possess certain theoretical value.

We show our main results and contributions. First, using a relatively large sample, this study provides further support for the effectiveness of the information disclosure ranking in reducing information asymmetry between enterprises and investors and reflects the degree of mispricing in emerging markets. Our results show that information disclosure ranking, industry production market competition and their interaction did influence the mispricing of Taiwanese firms between 2005 and 2014. Second, we find unique data that shows the SFI's measurements for information disclosure ranking are negatively associated with mispricing. It suggests that higher levels of information disclosure rankings (transparency) reduce agency problems, thus leading to lower mispricing. Third, we find that the benefits of increased information disclosure rankings levels are significant only for firms that face strong competition in the product market, compared to other firms in less competitive industries. Finally, we solve the endogeneity problem to improve the degree of mispricing, information disclosure may improve the information disclosure score as a result of decreased mispricing. In summary, the primary purpose of the evaluation system is to provide investors with a convenient pipeline for knowing the level of information disclosure of a company, thereby helping investors to make more informed investment decisions. However, the implementation of the system also indirectly forces enterprises to improve the quality of their information disclosure. The information disclosure evaluation system reduces information asymmetry between enterprises and investors and reflects the degree of mispricing. We argue that information disclosure rankings could facilitate managers' forward thinking, and firms with better information disclosure rankings or corporate social responsibility not only aim to reduce short-term mispricing but also focus on long-term sustainable development [32–39]. Moreover, information disclosure rankings firms are found to be more ethical [23,40], and managers are encouraged to undertake actions that boost long-term firm value, thus resulting in less mispricing.

This paper is structured as follows: the first section introduces the research background and literature review, the second section presents the hypothesis development, and the third section explains the sample and the definition of variables required in this study. The fourth section provides an analysis of the empirical results, and the final section presents conclusions drawn on the basis of the empirical findings of this study.

2. Hypothesis Development

2.1. Information Disclosure and Mispricing

Information disclosure is inextricably linked to mispricing. According to Hail [41], the effect of information pre-disclosure is favorable in developing markets because of relatively relaxed regulations and the lack of mandatory public rankings. Conversely, the trading market has higher levels of disclosure and a smaller discrepancy between real values and market expectations. Drake et al. [42] argued that because the quality of disclosed information improves the ability of investors to more accurately assess the sustainability of accruals and cash flow and their effect on future stocks, companies with higher-quality information disclosure experience less mispricing. Jiao [43] suggested that the amount of information disclosure is positively related to return on stocks, which may be because increased information transparency can correct mispricing. Kobayashi et al. [44] indicated that disclosure of patent information can significantly reduce risk and produce a relatively low standard deviation of 9.25%; in other words, disclosure of patent information helps to reduce mispricing. However, some scholars who have conducted research using news reports have reported contradictory results [40,45,46]. It demonstrate that inaccurate news reports make investors more critical and less likely to invest, resulting in mispricing and deviations in company value.

Through the implementation of the information disclosure evaluation system, we explore whether the increase in quality of information disclosure can effectively reduce information asymmetry between enterprises and investors and thus reduce mispricing. We present the following hypothesis:

Hypothesis 1 (H1). *Information disclosure rankings reduce mispricing.*

2.2. Effect of IDR on Mispricing under Different Levels of Industry Product Market Competition

Regarding supplementation and substitution of information disclosure, Bens [47] measured the amount of information that US companies voluntarily disclosed during 1990–1993 and discovered that significantly more information was disclosed when the SEC increased its supervision of restructuring companies at the end of 1993. He found that the positive relationship between amount of information disclosure and shareholder supervision indicates that supervision supplements disclosure.

Another study discerned a different relationship between information disclosure and product market competition. Healy and Palepu [48] suggested that voluntary company disclosure of information such as long-term strategic and nonfinancial indicators may increase the credibility of the financial reports of managers for competitive products. Increasing market disclosure may negatively affect the competitive position of companies. Similarly, Elliott and Jacobson [24] demonstrated that information disclosure can benefit public relations, such as by gaining the trust of investors and creditors. However, because potential competitors can acquire knowledge concerning marketing strategies, segment sales, production cost figures, technology, and management innovations from proprietary information, disclosure can increase competition and undermine the ability of a company to generate future cash flows. Giroud et al. [49] discovered that corporate merger laws weaken corporate governance by reducing the threat of hostile takeovers and prompting insufficient management. Giroud and Mueller [50] reported that in a noncompetitive industry, companies with weak governance are more likely to be investment targets for radical hedge funds, suggesting that investors actively mitigate inefficiencies. Ho et al. [23] investigated whether information disclosure is related to company value in markets with different levels of competition, revealing that information disclosure and product market competition levels affect company value. Consistent with the concept of competition to reduce management slack, companies in noncompetitive industries experienced a significant decline in business performance after the law was enacted, whereas companies in competitive industries were not significantly affected. We present the following hypothesis:

Hypothesis 2 (H2). *The negative relationship between information disclosure and mispricing is stronger for firms in competitive industries.*

3. Research Design

3.1. Sample Selection

Since 2005, the SFI has implemented a public IDTRS for listed companies, thereby determining the information transparency level of companies in the Taiwan stock market. This is based on the discussion of whether the publication of information transparency level forces enterprises to commit to the improvement of information disclosure. After the implementation of the evaluation system, we select the annual data of 10,686 SFI companies for the period from 2005 to 2014 as the research object. The final sample is selected on the basis of the following conditions, as determined by evidence: (1) To ensure data consistency, we omit annual data of enterprises that had not used the calendar system. (2) Furthermore, to estimate the degree of mispricing, we exclude industries with fewer than five sample counts for any year during the sample period. The sample variables used in this study are obtained from the CSMAR and Taiwan Economic Journal.

3.2. Variable Description

3.2.1. IDR Variable

IDRs and information transparency are major concerns in corporate governance. Foreign information disclosure level is assessed using the indices of Standard & Poor and Credit Lyonnais Securities regarding content concerning ownership, inverter, financial transparency, information disclosure, and board of director structure. The corporate governance ranking system has seven principles: management discipline, transparency, independence, accountability, responsibility, fairness, and social responsibility. Until 2014, the evaluation system for the ninth IDRs comprised scores from A++ to C− with seven ranking indices. To assess the level of corporate transparency, information ratings identified 114 indicators as evaluation criteria, which can be further grouped into five sub-categories: (1) compliance with the mandatory information disclosures; (2) timeliness of information reporting; (3) disclosure of financial forecast; (4) disclosure of annual report; and (5) disclosure of corporate website. Each disclosure indicator represents a "yes" or "no" question. One point is given to the question with a "yes" answer and zero otherwise. This study discusses information transparency by categorizing A++ to C− scores from 7 to 1. The 114 questions used to compile the IDR scores for each sample firm are presented in Pan et al. [46].

3.2.2. Industry Product Market Competition

The primary measure of product market competition used in this study is the Herfindahl–Hirschman Index (HHI). The HHI is computed as the sum of squared market shares [50–52]:

$$\mathrm{HHI_{jt}} = \sum_{i=1}^{N_j} S_{ijt}^2 \tag{1}$$

where S_{ijt}^2 is the market share of firm i in industry j in year t. A higher HHI indicates higher industry exclusivity, and a lower HHI reflects a greater likelihood of the industry being a competitive industry.

3.2.3. Mispricing

First, we use Equation (2) provided by Rhodes-Kropf et al. [53] and Chu et al. [40] to predict mispricing:

$$\ln(\mathrm{MV}_{ijt}) = \alpha + \beta_1 \ln(\mathrm{BE}_{ijt}) + \beta_2 \ln(\mathrm{NI}^{+}_{ijt}) + \beta_3 I_{<0} \ln(\mathrm{NI})^{+}_{ijt} + \beta_4 \mathrm{LEV}_{ijt} + \varepsilon_{ijt} \quad (2)$$

where $\ln(\mathrm{MV})$ is the natural logarithm of market capitalization, $\ln(\mathrm{BE})$ is the natural logarithm of book value of equity, and NI is the absolute value of net income. $I_{<0}$ is a dummy variable that has a value of 1 when the net income is negative and 0 otherwise. LEV is the leverage ratio, calculated as the debt of firm i divided by total assets.

Next, we use Equation (3) to compare corporate predicted and real value and estimate mispricing:

$$Mispricing_{it} = \ln[Real\ value_{it} / Predict\ value_{it}] \quad (3)$$

where *real value* is the market value of equity plus book value of debt and *predicted value* is the estimated market capitalization of predicted value obtained from Equation (2).

With reference to Berger and Ofek [54] and Chu et al. [40], we predict value by multiplying sales revenue by the median market value for a company in the industry during the sample year and dividing this product by the median sales revenue for the industry. We define mispricing as the value of the sample real market value divided by the predicted market value. A higher difference in value indicates greater mispricing.

3.2.4. Control Variables

We follow Pan et al. [46] to consider firm characteristics and agency-based proxies [40], including the natural logarithm of market capitalization (SIZE), ratio of debt to book value of assets (LEV), total number of annual trading days (Trading), institutional ownership (Inshd), number of analysts providing earnings forecasts (Analyst), illiquidity ratio (Liquidity), shareholding of directors and supervisors (SDS), shareholding of the largest shareholder (SLS), voting rights (TFV), and listed company (TSE). All variables are defined in Table 1.

3.3. Methodology

To assess the influence of IDR on mispricing, we use Equation (4) as follows:

$$\begin{aligned} Mispricing_{it} = {} & \beta_0 + \beta_1 \mathrm{IDR}_{it} + \beta_2 \mathrm{SIZE}_{it} + \beta_3 \mathrm{LEV}_{it} + \beta_4 \ln(\mathrm{Trading})_{it} + \beta_5 \ln(\mathrm{Inshd})_{it} \\ & + \beta_6 \ln(\mathrm{Liquidity})_{it} + \beta_7 \mathrm{SDS}_{it} + \beta_8 \mathrm{SLS}_{it} + \beta_9 \mathrm{TSV}_{it} + Time\ \mathrm{FE} \\ & + Industry\ \mathrm{FE} + \varepsilon_{it} \end{aligned} \quad (4)$$

where *Mispricing* is derived using the two estimation methods proposed by Berger and Ofek [54] and Rhodes-Kropf et al. [53] discussed in Section 3.2.3. *Time* FE is year fixed effects, and *industry* FE is industry fixed effects. These variables are defined in Table 1.

To provide further evidence, this study examines the effect of IDR on mispricing in industries with different levels of product market competition. According to the procedure developed by Giroud and Mueller [50], we use Equation (5) to perform estimates in this study:

$$\begin{aligned} Mispricing_{it} = {} & \gamma_0 + \gamma_1 (\mathrm{IDR}_{it} * \mathrm{HHI}_{it}) + \gamma_2 X_{it} + \gamma_3 \mathrm{SIZE}_{it} + \gamma_4 \mathrm{LEV}_{it} \\ & + \gamma_5 \ln(\mathrm{Trading})_{it} + \gamma_6 \ln(\mathrm{Inshd})_{it} \\ & + \gamma_7 \ln(\mathrm{Liquidity})_{it} + \gamma_8 \mathrm{SDS}_{it} + \gamma_9 SLS_{it} + \gamma_{10} TSV_{it} + Time\ \mathrm{FE} \\ & + Industry\ \mathrm{FE} + \varepsilon_{it} \end{aligned} \quad (5)$$

where HHI is a (3 × 1) vector of HHI dummies for high, medium, and low levels of industry product market competition. X denotes the control variables, which are HHI dummies for medium and low levels of industry product market competition.

Table 1. Definition.

Panel A: Variable definition				
Variable	**Explanation**			
Mispricing1	We use Rhodes-Kropf et al. [53] and Chu et al. [40] method to predict mispricing.			
Mispricing2	Market value of equity plus book value of debt to imputed value of total capital to sales for the median single-segment firm in industry and year [40,54].			
	Industry Characteristics			
HHI	Set the product market competition index as the dummy variable and use SALES as the measurement variable. If the HHI index is higher than the average HHI = 1 or else HHI = 0.			
	Firm Characteristics			
IDR	Information disclosure ranking score, ranging from 1 (the lowest, C−) to 7 (the highest, A++).			
ln(BE)	Natural logarithm of book value of equity.			
ln(NI)+	Natural logarithm of absolute value of net income.			
$I_{<0}$	It is 1 if the net income is negative, or else is 0.			
SIZE	Natural logarithm of market capitalization.			
LEV	The ratio of debt to book value of assets.			
ln(Trading)	Natural logarithm of total number of trading days in a year.			
ln(Inshd)	Institutional ownership = natural logarithm of stock ownership of foreign institutions, domestic funds, and securities companies.			
ln(1 + Analyst)	Natural logarithm of number of analysts providing earnings forecasts.			
ln(Liquidity)	Illiquidity ratio defined as natural logarithm of average daily absolute return divided by dollar trading volume in millions of a year.			
	Agency-based measurements			
SDS	Percentage of total outstanding shares owned by directors and supervisors.			
SLS	Percentage of total outstanding shares owned by largest shareholder.			
TFV	Times of seating to voting rights = seating rights %/voting rights %			
TSE	It is 1 if the listed company and 0 is OTC firm.			
Panel B: Measurements of information disclosure rankings based on five different dimensions [46]				
Dimension	**Item range**	**Total items**	**Percentage of total items represented**	**Items with extra rewards**
(1) Regulatory compliance	1–12	12	11%	None
(2) Timeliness of information disclosure	13–39	27	23%	9 items
(3) Disclosure of financial forecast	40–44	5	4%	5 items
(4) Disclosure of annual report	45–94	50	44%	4 items
(5) Disclosure of firm website	95–114	20	18%	20 items
Total			100%	38 items

3.4. Endogeneity Problem

This section details the endogenous relationship discovered between company information disclosure rankings and mispricing. In addition to improving the degree of mispricing, information disclosure may improve the information disclosure score as a result of decreased mispricing. However, although this study considers factors that may be related to the degree of deviation of information disclosure from corporate value and controls them to mitigate the problem of endogeneity [46,55,56], other endogenous links may exist. Therefore, this study uses a two-stage least squares method with instrumental variables (IVs) to address the endogeneity between information disclosure and mispricing [57–59].

In the selection of IVs, we adopt the method used by Cui et al. [60] and Gong and Ho [52,61] to consider changes in the first two periods of information disclosure (IDR_{t-1} and IDR_{t-2}) and the median information disclosure in each industry ($IDR_{Industry}$) and control other possible corporate governance IVs. We also apply the method presented by Chung et al. [14] and use the following criteria: proportion of shares owned by domestic trst funds (%DTF), family institutional investors (%FI), family-controlled foundations (%FF), and listed companies controlled by family directors (%FL); board independence (ID_Rate); listed companies (TSE); and changes in chairman of the board (Chairman_C), CEO (CEO_C), CFO (CFO_C), spokesman (Spokesman_C), and audit (Audit_C). The first stage of the least squares method entails using the method proposed by Larcker and Rusticus [62] to regress all selected exogenous IVs. The second stage entails the execution of least squares regression using the information disclosure ranking (IDR) valuation (IDR_{2SLS}) estimated in the first stage to identify any influence that helps to reduce the degree of mispricing. Equation (6) represents the first stage of the least squares method:

$$\begin{aligned}\mathrm{IDR}_{it} = {} & \lambda_0 + \lambda_1 \mathrm{IDR}_{i,t-1} \\ & + \lambda_2 \mathrm{IDR}_{i,t-2} + \lambda_3 \mathrm{IDR}_{Industry,t} + \lambda_4 \%\mathrm{DEF}_{it} \\ & + \lambda_5 \%\mathrm{FI}_{it} + \lambda_6 \%\mathrm{FF}_{it} + \lambda_7 \%\mathrm{FL}_{it} + \lambda_8 ID\_Rate_{it} + \lambda_9 \mathrm{Chairman\_C}_{it} \\ & + \lambda_{10} \mathrm{CEO\_C}_{it} + \lambda_{11} \mathrm{CFO\_C}_{it} \\ & + \lambda_{12} \mathrm{Spokeman\_C}_{it} + \lambda_{13} \mathrm{Audit\_C}_{it} + \lambda_{14} \mathrm{SIZE}_{it} + \lambda_{15} \mathrm{LEV}_{it} \\ & + \lambda_{16} \ln(\mathrm{Trading})_{it} + \lambda_{17} \ln(\mathrm{Inshd})_{it} + \lambda_{18} \ln(\mathrm{Liquidity})_{it} \\ & + \lambda_{19} \mathrm{SDS}_{it} + \lambda_{20} \mathrm{SLS}_{it} + \lambda_{21} \mathrm{TSV}_{it} + Time\ \mathrm{FE} + Industry\ \mathrm{FE} + \varepsilon_{it}\end{aligned} \tag{6}$$

3.5. Summary Statistics

As presented in panel A of Table 2, the IDRs of the sample firms are arranged from the lowest score 1 (C−) to the highest score 7 (A++). The average value of IDR is 3.59 and the median is 3. This indicates that the sample firms have lower than average IDRs. The mean and median of HHI are 0.16 and 0.11, respectively, suggesting that industry product market competition is generally high in all sample firms. Panel B of Table 2 presents the distribution of sample corporations according to industry product market competition. Among the 30 industries, we discover that the electronics industry constitutes two-thirds of the sample because this is a major industry in Taiwan. However, some corporations are in oligopoly industries and are involved in the production of cement, food, electric cables, glass ceramics, paper, auto parts, other electronics, oil, gas, or electricity.

Table 2. Summary statistics.

Panel A: Summary statistics of all firms					
	MEAN	**STD**	**Q1**	**MEDIAN**	**Q3**
IDR	3.59	1.18	3.00	3.00	5.00
Mispricing1	0.00	0.43	−0.27	−0.08	0.18
Mispricing2	0.00	0.79	−0.46	−0.03	0.42
HHI	0.16	0.17	0.08	0.11	0.18
SIZE	15.53	1.59	14.43	15.27	16.28
LEV	1.27	2.79	0.39	0.73	1.21
ln(Trading)	5.57	0.17	5.51	5.52	5.53
ln(Inshd)	2.91%	5.77%	0.00%	0.30%	3.50%
ln(1 + Analyst)	1.18	1.33	0.00	0.69	2.20
ln(Liquidity)	0.05%	0.19%	0.00%	0.00%	0.01%
SDS	23.10	14.28	12.62	19.53	29.81
SLS	19.75	11.53	11.77	17.74	25.55
TSV	23.86	17.43	9.90	19.94	34.33

Table 2. *Cont.*

Panel B: Summary statistics of all industries			
Classification	**Industry**	**Industrial concentration level**	**HHI**
1	Cement	Oligopoly	0.42
2	Food	Oligopoly	0.39
3	Plastics	General	0.21
4	Textile	General	0.20
5	Electric machinery	General	0.15
6	Electric cables	Oligopoly	0.32
7	Chemical industry	Competition	0.08
8	Biotechnology and medical care	Competition	0.06
9	Glass ceramic	Oligopoly	0.51
10	Paper	Oligopoly	0.28
11	Steel	General	0.21
12	Rubber	Oligopoly	0.25
13	Auto	Oligopoly	0.26
14	Semiconductor	Competition	0.10
15	Computer peripherals	Competition	0.11
16	Photoelectric	Competition	0.12
17	Communications network operator	Competition	0.11
18	Electronic components	Competition	0.03
19	Electronic access	Competition	0.12
20	Information services	Competition	0.09
21	Other electronics	Oligopoly	0.74
22	Building material and construction	Competition	0.04
23	Shipping	General	0.16
24	Sightseeing	General	0.13
25	Finance and insurance	General	0.15
26	Trade department	General	0.20
27	Securities	General	0.15
28	Culture	General	0.22
29	Oil, gas and electricity	Oligopoly	0.85
30	Other	General	0.13

Note: This table reports descriptive statistics of explanatory variables, industry characteristics, firm characteristics, and agency-based proxies for sample firms. The definitions of the variables are shown in detail in Table 1.

To identify potential multicollinearity among the explanatory variables, we examine the correlations and variance inflation factor among all independent variables. Table 3 indicates that there are no multicollinearity problems.

Table 3. Correlation matrix.

	VIF	**IDR**	**HHI**	**SIZE**	**LEV**	**ln(Trading)**	**ln(Inshd)**	**ln(1 + Analyst)**	**ln(Liquidity)**	**SDS**	**SLS**	**TSV**
IDR	1.13	1.00										
HHI	1.04	−0.01	1.00									
SIZE	2.17	**0.31**	**0.04**	1.00								
LEV	1.45	**0.16**	**−0.02**	**0.49**	1.00							
ln(Trading)	1.22	**0.05**	**−0.05**	**0.19**	**0.03**	1.00						
ln(Inshd)	1.29	**0.22**	**0.06**	**0.42**	**0.30**	**0.05**	1.00					
ln(1 + Analyst)	1.56	**0.16**	**−0.08**	**0.51**	**0.07**	**0.22**	**0.26**	1.00				
ln(Liquidity)	1.13	**−0.05**	**−0.02**	**−0.07**	**0.03**	**0.29**	**−0.04**	**−0.07**	1.00			
SDS	1.53	**−0.01**	**0.11**	**−0.11**	**0.01**	**−0.16**	**0.05**	**−0.13**	**−0.04**	1.00		
SLS	1.56	**−0.03**	**0.00**	**−0.02**	**0.04**	**−0.08**	**0.00**	**−0.13**	**−0.01**	**−0.17**	1.00	
TSV	1.83	**−0.11**	**0.10**	**−0.13**	**0.01**	**−0.13**	**−0.08**	**−0.23**	**−0.03**	**0.40**	**0.45**	1.00

Note: This table reports the Pearson correlation coefficients and Variance Inflation Factor (VIF) between independent variables. The definitions of the variables are shown in detail in Table 1. The boldfaced numbers denote statistical significance below 10%.

4. Empirical Results

4.1. Effect of IDR on Mispricing

In this study, we refer to the methods presented by Berger and Ofek [54], Rhodes-Kropf et al. [53], and Chu et al. [40] to estimate the degree of mispricing of the sample companies. In Table 4, empirical results reveal the effect of IDR on the degree of mispricing; the coefficient is −0.008 (t-statistic = −2.64) in the Mispricing1 regression and −0.032 (t-statistic = −5.04) in the Mispricing 2 regression. The IDR score is significantly representative because the different methods for estimating the degree of mispricing all maintain a significance level of less than 1%, even after we control for both the year and industry fixed effects. Therefore, we standardize annual IDRs by using the following formula: (original IDR—average annual information disclosure)/standard deviation of IDRs. The standard deviation of IDRs is calculated from the standardized information disclosure score. This result is consistent with those of previous analyses [46]. The regression analysis results verify that IDRs effectively reduce the degree of mispricing, which supports the findings of Lee and Lee [45] and Chu et al. [40]. The higher quality is the disclosed information, the better investors can evaluate firms, and hence the stock price is closer to the firm's true fundamentals. On the other hand, if the information disclosed to investors is inaccurate, incomplete, late or even fraudulent, the market valuation will hardly be accurate hence the stock price is likely to deviate much form the firm's true fundamental.

Table 4. Effect of IDR on mispricing.

Dependent Variable	Mispricing1	Mispricing2
Intercept	1.713 ***	1.539 ***
	(14.37)	(6.18)
IDR	−0.008 ***	−0.032 ***
	(−2.64)	(−5.04)
SIZE	−0.121 ***	−0.105 ***
	(−37.23)	(−15.57)
LEV	0.073 ***	0.036 ***
	(38.98)	(9.31)
ln(Trading)	−0.005	0.031
	(−0.23)	(0.75)
ln(Inshd)	0.183 ***	1.373 ***
	(2.93)	(10.56)
ln(1 + Analyst)	0.114 ***	0.071 ***
	(34.24)	(10.27)
ln(Liquidity)	−13.617 ***	−14.129 ***
	(−6.78)	(−3.37)
SDS	0.002 ***	0.001
	(6.59)	(1.39)
SLS	0.002 ***	0.006 ***
	(6.45)	(7.90)
TSV	−0.001 ***	0.000
	(−4.83)	(−0.57)
Year FE	YES	YES
Industry FE	YES	YES
Adj R^2	0.43	0.18
N	10,686	10,686

Note: This table reports the impact of IDR on mispricing. All models are based on Equation (4). The definitions of the variables are shown in detail in Table 1. The t-statistics are based on standard errors clustered by industry and year and reported in the parenthesis. *, **, *** denote statistical significance at 10%, 5%, and 1%, respectively.

4.2. Effect of IDR on Mispricing in Industries with Different Levels of Product Market Competition

Table 5 presents the results of investigating the effect of IDR on the degree of mispricing in industries with different levels of market competition (HHI). We conduct a test using the method presented by Giroud and Mueller [50]. The empirical results indicate a (3 × 1) vector interaction between IDR and HHI, and the HHI can be divided into three distinct groups: high HHI (33%), median HHI (34%), and low HHI (33%). In Mispricing1, the coefficient for the interaction between IDR and HHI (high) is −0.006 (t-statistic = −0.83), that for the interaction between IDR and HHI (median) is 0.006 (t-statistic = 1.38), and that for the interaction between IDR and HHI (low) is −0.019 (t-statistic = −4.69). The Mispricing2 regression indicates that the (3 × 1) vector coefficient for the interaction between IDR and HHI (high) is −0.025 (t-statistic = −1.59), that for the interaction between IDR and HHI (median) is −0.010 (t-statistic = −1.04), and that for the interaction between IDR and HHI (low) is −0.049 (t-statistic = −5.75). All interactions between IDR and HHI (high or median) are nonsignificant, and the interaction between IDR and HHI (low) is significantly negative. IDRs do not exhibit an influence on mispricing in oligopoly industries. However, regarding the interaction between IDR and the lowest HHI (competitive industries), financial risk and default probability are higher for these industries compared with others; therefore, investors should consider information transparency prior to investing. If a firm has higher information disclosure quality, then investors will have more confidence when investing in the firm, which reduces mispricing.

Table 5. The impact of IDR on mispricing under different industry product market competition level.

Dependent Variable	Mispricing1	Mispricing2
Intercept	1.801 ***	1.650 ***
	(15.00)	(6.58)
IDR*HHI(high)	−0.006	−0.025
	(−0.83)	(−1.59)
IDR*HHI(median)	0.006	−0.010
	(1.38)	(−1.04)
IDR*HHI(low)	−0.019 ***	−0.049 ***
	(−4.69)	(−5.75)
HHI(median)	−0.137 ***	−0.177 ***
	(−5.56)	(−3.42)
HHI(high)	−0.104 ***	−0.168 **
	(−2.71)	(−2.09)
SIZE	−0.120 ***	−0.105 ***
	(−37.21)	(−15.56)
LEV	0.073 ***	0.036 ***
	(38.91)	(9.25)
ln(Trading)	−0.007	0.028
	(−0.33)	(0.68)
ln(Inshd)	0.195 ***	1.388 ***
	(3.13)	(10.67)
ln(1 + Analyst)	0.113 ***	0.070 ***
	(33.87)	(10.08)
ln(Liquidity)	−13.881 ***	−14.414 ***
	(−6.92)	(−3.44)
SDS	0.002 ***	0.001
	(6.54)	(1.36)
SLS	0.002 ***	0.006 ***
	(6.50)	(7.93)
TSV	−0.001 ***	0.000
	(−4.85)	(−0.55)
Year FE	YES	YES
Industry FE	YES	YES
Adj R^2	0.43	0.18
N	10,686	10,686

Note: This table reports the impact of information disclosure ranking on mispricing under different industry product market competition levels. All models are based on Equation (5). The definitions of the variables are shown in detail in Table 1. The t-statistics are based on standard errors clustered by industry and year and reported in the parenthesis. *, **, *** denote statistical significance at 10%, 5%, and 1%, respectively.

4.3. Tests of the Endogeneity Effect

Table 6 presents the results obtained from the use of the two-stage least square method to solve the problem of endogeneity. We use the method proposed by Larcker and Rusticus [62] to regress all selected exogenous IVs in the first stage of the least squares regression to estimate IDRs. The IDRs estimated in first stage of the least squares regressions are then used to evaluate the effect of IDR on mispricing. Using the methods presented by Chung et al. [14] and Cui et al. [60], we regress IVs on IDRs in the first stage of the least squares regression. We discover that the coefficient of the estimated IDRs in the second-stage regression on Mispricing1 is −0.008 (t-statistic = −1.76). In the Mispricing2 regression, the coefficient of the estimated IDRs is −0.048 (t-statistic = −5.16). The empirical results indicate that the IDRs estimated using IVs significantly reduce mispricing. Moreover, we use this method to solve the problem of endogeneity. Another analysis confirms the robustness of this result. According to the method presented by Gong and Ho [61], we use the Generalized Method of Moments (GMM) approach to solve the problem of endogeneity, and the consistent results support our findings.

Table 6. Two-stage least squares (2SLS) regression analysis for the relationship between mispricing and IDR.

Dependent Variable	First Stage: IDR	Second Stage: Mispricing1	Second Stage: Mispricing2
Intercept	−1.976 *** (−5.13)	1.569 *** (12.17)	1.434 *** (5.26)
IDR_{t-1}	0.635 *** (69.73)		
IDR_{t-2}	0.119 *** (13.41)		
$IDR_{Industry}$	0.727 *** (12.74)		
%DTF	0.000 (−0.11)		
%FI	0.001 (1.00)		
%FF	0.001 (0.61)		
%FL	0.002 (1.45)		
ID_Rate	0.080 * (1.87)		
Chairman_C	−0.005 (−0.17)		
CEO_C	0.014 (0.63)		
CFO_C	−0.001 (−0.03)		
Spokeman_C	0.004 (0.19)		
Aduit_C	−0.040 ** (−2.21)		
TSE	−0.103 *** (−5.25)		

Table 6. *Cont*.

Dependent Variable	First Stage: IDR	Second Stage: Mispricing1	Second Stage: Mispricing2
IDR_{2SLS}		−0.008 *	−0.048 ***
		(−1.76)	(−5.16)
SIZE	0.056 ***	−0.120 ***	−0.105 ***
	(6.05)	(−33.79)	(−13.97)
LEV	−0.010 **	0.075 ***	0.042 ***
	(−2.21)	(36.72)	(9.65)
ln(Trading)	−0.095 *	0.018	0.056
	(−1.92)	(0.85)	(1.23)
ln(Inshd)	0.279 *	0.256 ***	1.507 ***
	(1.75)	(3.78)	(10.52)
ln(1 + Analyst)	0.024 ***	0.107 ***	0.062 ***
	(2.83)	(28.88)	(7.96)
ln(Liquidity)	−3.517	−16.966 ***	−17.544 ***
	(−0.62)	(−6.90)	(−3.37)
SDS	0.000	0.002 ***	0.002 ***
	(0.39)	(7.42)	(2.84)
SLS	0.000	0.003 ***	0.007 ***
	(0.20)	(6.74)	(8.09)
TSV	−0.001	−0.001 ***	−0.001
	(−1.57)	(−5.22)	(−1.26)
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Adj R^2	0.63	0.42	0.17
N	9071	9071	9071

Note: The table reports the two-stage least squares (2SLS) regression analysis results for examining whether information ranking explains mispricing. All models are based on Equation (6). The definitions of the variables are shown in detail in Table 1 and Section 3. The t-statistics are based on standard errors clustered by industry and year and reported in the parenthesis. *, **, *** denote statistical significance at 10%, 5%, and 1%, respectively.

5. Conclusions

After Enron acquired a substantial debt risk, WorldCom, Tyco, and Merck were also involved in accounting scandals that not only caused an increase in the stock market margin but also reduced investor confidence. This study uses the IDR indicators established by the SFI to divide the IDR score into seven points. During the sample period of 2005 to 2014, we obtain the data of 10,686 listed companies. This study reveals that the information disclosure work evaluation system promoted by the SFI and IDR significantly affects the quality and amount of information disclosed by the evaluated enterprises. Moreover, the empirical results of this study reveal that the transparency indicator of information disclosure helps to reduce the degree of mispricing. Considering the disadvantages of low liquidity and high capital costs that may accompany low information transparency, companies focusing on information disclosure will eventually reduce their degree of mispricing.

From the perspective of the external environment, the size and transparency of the monopolistic industry will help reduce the mispricing of enterprise value. Additionally, this study provides further evidence that industry product market competition is separated into three groups. Negative relationships between IDR and mispricing are only observed in competitive industries because of their relatively high financial risk and default probability, which prompts investors to consider information transparency. If a firm increases their information transparency, investors will have more interest and confidence in investing in the firm, leading to reduced mispricing. This evidence supports the notion that IDRs effectively reduce mispricing in competitive industries. Policies related to the promotion of information disclosure outside of the SFI can also be affirmed using our results. Moreover, information disclosure ranking firms are found to be more ethical, trustworthy, and honest, and managers are encouraged to undertake actions that boost long-term sustainable development, thus resulting in less mispricing.

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Organizational Climate and Work Style: The Missing Links for Sustainability of Leadership and Satisfied Employees

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Abstract: People try to find the role of government in today's modern society. Citizens of any country look forward to benefit from government services. Although the government implements laws and policies in all areas of society, people only know about it through government's services. We describe a good government's service of organization, department, unit, and division that has an appropriate human strategy. **Purpose:** Purpose of this study is to investigate which factors have been missing that connects and maintains the sustainability between the leadership style and employees' satisfaction in the government sector of Mongolia. More specifically, the purpose of the study is to investigate the missing link between leadership style and job satisfaction among Mongolian public sector employees. This study reiterates the mediating role of organizational climate (OC) and work style (WS) in a new proposed model. **Methodology:** The questionnaire is designed by a synthesis of existing constructs in current relevant literature. The research sample consisted of 143 officers who work in the primary and middle units of the territory and administration of Mongolia. Factor analysis, a reliability test, a collinearity test, and correlation analyses confirm the validity and reliability of the model. Multiple regression analysis, using Structural Equation Modeling (SEM), tests the hypotheses of the study. The sample of this study is chosen from the public organization. Mongolia is a developing country. This country needs good public leaders who can serve citizens. This study will be extended further. In addition, Mongolia really needs sufficient studies. **Practical implications:** This study has several important implications for studies related to organizational behavior and job satisfaction. Furthermore, the implications of these findings are beneficial to organizations aimed at improving policies and practices related to organizational behavior and human resource management. Regulators and supervisors of private or public organizations aiming to increase the level of their employees' job satisfaction will also benefit from the findings. Therefore, this study's new proposed model can be the basis of fundamental research to build a better human resource policy. Although the leadership style is an influential factor for job satisfaction, this study identifies the mediating missing links between the leadership style and employees' job satisfaction. **Findings:** The findings of this research indicate that the organizational climate and work style complement and fully mediate the relationship between leadership style and job satisfaction. An appropriate leadership style is most effective when it matches the organizational climate as well as employees' work style. Furthermore, a suitable organizational climate will increase the level of job satisfaction.

If the work style of employees is respected and taken into consideration, the leadership style can find its way into job satisfaction. **Originality/value:** This study is the first to understand the motivators of job satisfaction in the government sector of Mongolia. This study suggests valuable findings for executive officers who are junior and primary unit's officers of the register sector of government in Mongolia. The findings of this study help managers and executives in their effort develop and implement successful human resource strategies.

Keywords: job satisfaction (JS); work style (WS); leadership style (LS); organizational climate (OC); register office; Mongolia

JEL Classification: D23; J01; J24; J28; J45; J53; J81; M12

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1. Introduction

In Mongolia, it is more likely for the job seekers to pursue employment in government sectors such as a register office than in private companies. Young graduates encouraged by their parents are urged to become a civil servant and to seek a position in the government. Although satisfaction with the organizations is one of the most crucial factors in the sustainability of private companies [1], it does not seem to be the same situation in public sector organizations. Often, a low level of job satisfaction is observed in public sector organizations. Buchanan [2] and Lachman [3] concluded that employees in the public sector are less satisfied with their work than private companies' employees do. Employees who work in primary units of government or in provinces are less satisfied with their leader/supervisors. Efficient leadership and management style can help increase employee satisfaction [4].

While the public sector organization has been receiving increasing attention in the last two decades, little research focuses specifically on the job satisfaction of the registration organization [5]. In this sector, there is still a lack of performance appraisal, employee job satisfaction, workload balance, and a healthy subordinate-supervisory relationship. The registration organization in Mongolia, especially the primary administrative units and provinces, is less technologically resourced largely due to a vertical organizational structure and underpaid employees. The organizational climate seems to depend also on the particular characteristics of the work environment [4,6–8]. Employees should realize the positive organizational importance and they should create it for success.

Job satisfaction literature has been studied in private sector organizations. Recent empirical studies have looked at service industries and service firms [9]. To our knowledge, there are almost no empirical studies exploring the employees' job satisfaction in the Mongolian public organization in the government register sector. Our study includes registrars, inspector, and administrative staff of the Mongolian register organization. In this sector, there are no contemporary studies of registrars' job satisfaction. None of the previous studies looked at the influence leadership style on job satisfaction through the organizational climate and work style. The current study is an attempt to address this gap in the literature. We hypothesized that the leadership style with the presence of the organizational climate and work style has no direct effect on job satisfaction. However, the leadership style through the organizational climate and work style will have an indirect effect on employees' job satisfaction. In this study, we aim to investigate how the leadership style through meditating factors, synchronously and asynchronously, influence job satisfaction of registration organization employees. The organizational climate and work style are synchronous mediators since they work in parallel to influence the relationship between leadership style and job satisfaction. The organizational climate and work style also mediate the relationship between leadership style and job satisfaction synchronously as they work in series. Figure 1 depicts visually the synchronous and asynchronous influences of the mediators.

2. Literature Review and Hypotheses Development

This section reviews motivator factors used in this paper including work style, leadership style, and organizational climate studies relevant to job satisfaction. In addition, the relationship among the variables leading to the development of the hypotheses is discussed.

2.1. Leadership Style (LS)

Leadership is one of the main factors for success [10] in any kind of group activities. The leadership style inspires people with a specific vision to work, helps clarify some concrete goals, and motivates and helps employees communicate well within their team. Wilkinson and Wagner [11] show that the leaders' significant support influences employees' attitude. According to Drucker [12], the style of leadership is an engine of effective organization and it is based on the interaction between leader and employees in the workplace. Furthermore, Edgar and Geare [13] argue that the workers-leader relationship is a key factor that influences workers' satisfaction in their workplace. In this regard, the leader represents his/her employees and lets employees assess their leader.

Alola, Avci, and Ozturen [14] study the effect of leadership style on job satisfaction in the Nigerian tourist industry. The results show that the leadership style affects hotel employees' job satisfaction. Transformational Leadership emphasizes an increasing work commitment, job satisfaction, and well-being of the employees [15,16]. Authentic Leadership depends on the organizational context and an individual's positive psychological attitude. This type of leadership determines self-awareness and self-regulated positive behaviors of both leaders and employees. Entrepreneurial leadership converges and directs the group members' performances toward the attainment of organizational objectives that involves identifying and implementing entrepreneurial opportunities [17]. The following sections discuss and define the variables of this study.

2.2. Organizational Climate (OC)

According to McGregor [18], the organizational climate is defined as how employees perceive organizations' internal functions like decision-making and rule-setting in the workplace. It can also be defined as a set of behaviors that describe an organization [19]. An organizational climate can be specific for each organization. It may make an organization different from other organizations and influence employees' work behavior in the organization. The organizational climate can also leave a perception in the employees' mind towards the management of their working unit [20]. It is related to employees' perceptions on their own and other colleagues' effectiveness in job and task implementation. In organizations that are public or private where employees' perception of their organizational climate is more egoistic and less ethical, employees are more prone to corruption [21].

Griffin [22] suggests that the climate generally refers to direct perceptions of the work environment. Organizations need a positive climate in their workplace to boost employee motivation and raise the opportunity that employees will implement adequate efforts doing their tasks. Therefore, a positive climate encourages employees' productivity and decreases turnover. Thus, it is vital for business success. Chang, Wu, and Liu [23] collected data from 34 human resources managers and 354 employees working in the Chinese manufacturing and service industries. Their results demonstrate that work style and workplace events influence employees' job satisfaction. A three-year study (2007, 2009, 2010) of 5656, 6274, and 5841 public employees facilitated by the Ministry of Labor and Social Security of Spain indicates that the organizational climate is among the top five influential factors of job satisfaction among the employees [24].

According to Jung, Chow, and Wu [25] and Jung and Ali [26], the organizational climate is one of the most important characteristics of a great and comfortable workplace. Therefore, if a leader can create a great workplace, it will increase employees' productivity. Several studies [27–29] point out the positive impact of leadership style on the organizational climate. There is, however, a lack of research with the Mongolian population and specifically Mongolian government employees. Therefore, in this paper, we follow the previous study's suggestions to make the following hypothesis for LS and OC for Mongolian register office employees.

H1. *LS has a positive association with OC.*

2.3. Work Style (WS)

There are several definitions of work styles proposed by researchers. Mihut [30] suggests that the work style is the combination of professional, organizational, political, and moral qualities expressed in daily professional activities of individuals. Dawis and Lofquist [31] define work styles as an employee's originally conceived working attributes. These traits are generally established in childhood through experimentation, which crystallized in adulthood and declined due to the aging process. Subsequently, an individual might possess the appropriate skills and abilities to meet the demands of the job. However, if the work style is ineffectively communicated or perceived, the job environment satisfies neither the employer nor the employee. Work styles, thus, have an impact for job satisfaction [31,32]

Niculiţă [33] has observed the relationship between work style and organizational climate in the scope of Romanian employees. He found that there are several factors in an organizational climate that can influence some specific work style factors such as a positive interpersonal relationship, a positive motivation, an effective and efficient management in an organization, and organizational support. Therefore, the organization climate has a significant impact on work style. In this paper, we follow his suggestion to make the following hypothesis for OC and WS for Mongolian register office employees.

H2. *OC has a positive association with WS.*

2.4. Job Satisfaction (JS)

In organizational behavior studies, there are numerous definitions of job satisfaction. Locke [34] defines employee's satisfaction to be the positive emotional state stemming from the evaluation of a person's experience associated with the job. According to Spector [35], job satisfaction is the degree to which one likes his or her job. However, Brief's [36] job satisfaction represents an attitude towards the job. Mathieu and Zajac [37] and Hirschfeld, Field, and Bedeian [38] define the term to be the result of some factors that affect the quality of individuals' working life. On the other hand, Altuntas and Baykal [39] state that job satisfaction is of interest to employers. Job satisfaction continues to be studied since it is considered to be a desirable outcome of employment [39]. This study is based on previous findings and the notion introduced by Durst and DeSantis [40] that employee's satisfaction is important in public sector employees who are often perceived as unhappy workers. Their low morale may be associated with low productivity.

Job satisfaction is an important factor in an organization that the absence of it can lead to team's lethargy and a lack of enthusiasm so that it may reduce organizational commitment. If there is a lack in job satisfaction, it may cause some good employees to quit their jobs [41].

Many studies have observed the positive relationship between work style and job satisfaction. For example, Dawis and Lofquist [31] shows that work style positively influences job satisfaction. They found that, even though employees have the appropriate skills and abilities to meet the demands of their jobs and their work style is ineffectively expressed, their manager would not be fully satisfied with their performance. Thereby, it is necessary for employees to have a decent work style in order to make their manager/leader satisfied with their performance. Empirical studies by Arbuckle et al. [42], Chang et al. [43], Chuang et al. [44], Harley et al. [45], Harmon et al. [46], and Young et al. [47] show that a high-performance work system has been connected with higher employee satisfaction. Fan et al. [48] indicated that the high level of adoption would increase job satisfaction. Based on the information above, in this paper, we follow previous studies' suggestions to make the following hypothesis for OC and WS for the Mongolian register office employees.

H3. *WS has a positive association with JS.*

2.5. Mediators between Leadership Style and Job Satisfaction

The relationship between leadership style and job satisfaction is one of the most critical factors for success in an organization [49,50]. Several studies have looked at this relationship and established the significant influence of leadership style on job satisfaction [49,51–53]. Some studies went beyond and looked at the intermediary influence of the organizational climate [54]. Jung and Ali [26] look at the influence of organizational climate as the moderator between corporate social responsibility and job satisfaction.

Leadership style and the organizational climate have been reported to positively and significantly influence employee satisfaction [55]. Priyankara et al. [56] reported on employees of textile and apparel manufacturing factories in Sri Lanka. Their findings indicate that the organizational climate is the partial mediator between leader's support and employee behavior. Experimental evidence from the Alola, Avci, and Ozturen [14] study in Nigeria shows that work style mediates the relationship between leadership style and job satisfaction. In this paper, based on the previous findings, we made the following hypothesis for LS and JS with OC and WS as mediators for Mongolian register office employees.

H4. *OC mediates the relationship between LS and JS.*

H5. *WS mediates the relationship between LS and JS.*

H6. *OC and WS are serial multiple mediators between LS and JS.*

2.6. Mediator between Leadership Style and Work Style

Leaders have their own leadership style towards their employees while each employee also has their individual work style [33]. Work style is the accumulation of personalized work-related experiences. Different definitions of work style result in typologies with different theoretical or applied values. For example, Scherpereel and Bowers [57] have designed several workshops that aim to help create work teams based on heterogeneity and complementarity. In their approach, work style during teamwork consists of four different classifications: doers, expressive, amiable, and analytics works. These work styles together have strong correlation with leadership style. Work style in the organization depends on leadership style [33]. Leaders have their own leadership style to lead their employees. In addition, the style of work offered in different organizations may not be the same [58–60]. Sarros et al. [61] examined the relationship between leader's behavior (transactional and transformational styles) and aspects of an organization's structure (i.e., centralization, formalization dimensions). In this paper, we hypothesize that organizational culture is the mediator that has not been studied previously. The following hypothesis for LS and WS with OC as the mediator for Mongolian register employees.

H7. *OC mediates the relationship between LS and WS.*

2.7. Mediator between Organizational Climate and Job Satisfaction

Many studies have observed a positive relationship between the organizational climate and job satisfaction. For example, Chen and Spector [62], Brockner [63], and De Cremer [64] have shown that negative leader-employee interactions have a negative influence on the employees' satisfaction, which results in signs of stress and unwillingness to go to work. Tsai [65], Hashemi and Sadeqi [41], Ángel Calderón Molina et al. [66], and Ahmad et al. [67] predict that the organizational climate has a significant effect on job satisfaction. In this paper, we introduce work style as a mediator. The organizational climate is also related to employee corruption [21]. We mentioned that organizational climate influences work style. We also established that work style has a positive association with job satisfaction. Based on previous research findings, we make the following hypothesis for OC and JS with WS as the mediator for Mongolian register employees.

H8. *WS mediates the relationship between OC and JS.*

3. Research Methodology

3.1. Sample Selection and Instrumentation

This paper uses a convenient sampling technique in which we select the registration sector of Mongolian government units accessible via postal mail or email. Data is gathered from 143 employees who are working in primary and middle units of administration in the Mongolian registration offices. The survey questionnaires of this paper are fundamentally built by the features that are chosen based on the considerations of the research framework, definitions of the variables, and literature reviews. Most of the items of the instrument are based on questions used in previous research. Some questions are used in their original form while others are slightly modified to address the specific nature of this study. In the design of a questionnaire for our survey, a complex construct is used in order to enrich both the meaning and multi-dimensionality.

3.2. Data Analysis Procedure

Structured and unstructured observations are used in this study. After collecting some information relevant to the Mongolian government's structure and administration, sample data is collected from the registration organization's primary and middle units of the Mongolian government. Second, the interview method is used in this study before the sample is collected. The data is collected from leaders/supervisor of government employees of the register office of Mongolia. Questions are based on theoretical and previous empirical studies and the result of the observation and interviews. Method of analysis of the sample is a quantitative method. Based on the proposed research model, the quantitative model is the best suitable method to draw conclusions utilizing techniques that emphasize the validity and the reliability.

3.3. Theoretical Framework and Hypotheses

The framework below shows the study hypotheses, which examines the interrelationships between examination variables. The framework hypothesizes that leadership style (LS), the organizational climate (OC), and work style (WS) influences job satisfaction (JS). The model depicted in Figure 1 suggests that job satisfaction (JS) is the endogenous variable, which is influenced by leadership style (LS) as an exogenous variable. Moreover, the effect of LS on JS is mediated by the organizational climate (OC) and work style (WS) or $\eta = f(\xi1, \xi2, \xi3)$. Where η is job satisfaction (JS), $\xi1$ will be leadership style (LS), $\xi2$ will be the organizational climate (OC), and $\xi3$ will be the work style (WS). OC and WS are not only the endogenous variables but also the mediators for η. Therefore, job satisfaction is a dependent variable (DV) that is influenced by the independent variables' leadership style (LS) and the mediating variables' organizational climate (OC) and work style (WS). The equation is visualized in Figure 1.

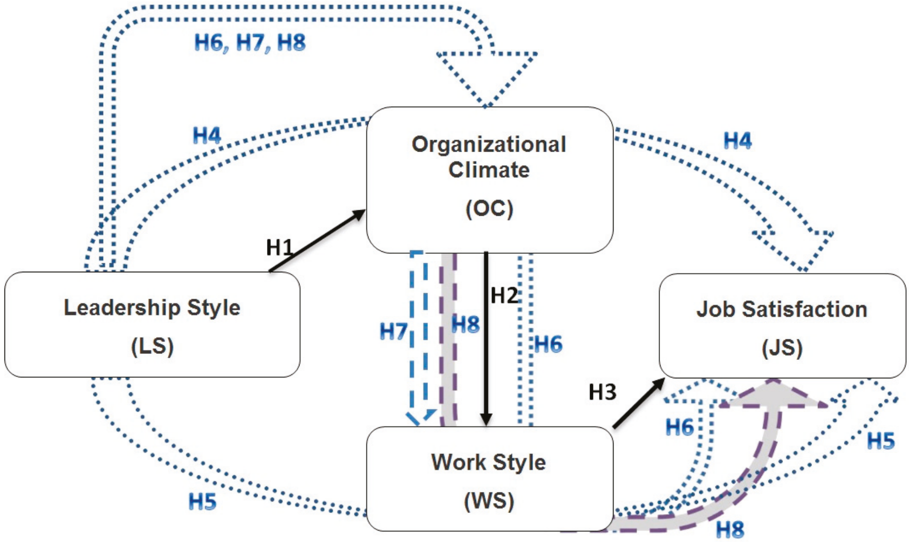

Figure 1. Research framework.

4. Results and Findings

A total of 200 questionnaires were distributed to employees of the register organization and 143 questionnaires were collected for this study. This paper studied a case and illustrated the demographics of respondents.

4.1. Demographic Characteristics

Eight major categories are computed to identify all the characteristics of the participants of this study. Demographics have shown that 23.1% of the respondents are male and 76.9% of the respondents are female. The profile of respondents exhibited the frequency and percentage of age dispersion, which was divided into five categories. The majority of the respondents are aged between 25–34 years old (44.8%), which is followed by respondents aged 35–44 years old (37.1%), 45-to-55 years olds (15.4%), and employees aged under 24 are 4 (2.8%). In terms of the occupation, most of the respondents are lawyers (58 = 40.6%). There are also other occupation types (47 = 32.9%) and economists (26 = 18.2%). These are related to the gender category. The highest percentage of respondents have a Bachelor's degree (74.8%), which is followed by a Master's degree (24.5%), and a Ph.D. and up is composed of only 0.7%. Work duration in the register office is grouped into four categories. Most of the respondents have 0–5 years of experience (61 = 42.7%), which is followed by 6–10 years (55 = 38.5%), 11–15 years (21 = 14.7%) and then 16 years and more (6 = 4.2%). The salary is divided into four categories: 46.9% of respondents have a salary with less than $300 USD per month, which is followed by $301–500 USD (39.9%), $501–500 USD (12.6%), and respondents with a salary range of more than $701 USD (0.7%). From other descriptive statistics, most of the respondents are living in an apartment (68 = 47.6%), which is followed by a private house (33 = 23.1%), a rental (30 = 21%), and respondents who live in a Mongolian traditional house (12 = 8.4%). Final demographic information is working hours per day, which is partitioned into three measurements: 84 (58.7%) of respondents work 9–12 h, which is followed by 53 (37.1%) respondents who work 8 h in a day, and then 6 people responded that they work 13 h and up. This occupied only 4.2% of all respondents for this research.

4.2. Test of Reliability and Validity

Exploratory factor analysis (EFA) is an important tool for organizational researchers. It can be useful for refining measures, evaluating construct validity, and testing hypotheses. The general suggestion that, in order to get a good model, factorability of the Kaiser-Meyer-Olkin Measure of sampling adequacy (KMO) must be greater than 0.6, communality values must be greater than 0.5, eigenvalues must be greater than 1, and factor loadings should be at least 0.5 or higher [68].

From Table 1, all factor loadings are found to be higher than 0.5. KMO is 0.915, which is higher than 0.6. Thus, the validity of the instrument for this study passed the Bartlett's Test of Sphericity. All factors have an Eigenvalue of 1 or greater. As shown in Table 1, reliability coefficient of each factor as well as the whole instrument is higher than the acceptable level of ($\alpha \geq 0.7$). All factor loadings are above 0.7. In short, the results shown in Table 1 indicate that all factors are valid and reliable. Thus, we can further conduct additional statistical analysis, which is discussed in the next subsections.

Table 1. Factor Analysis, Instrument Validity, and Reliability.

Variables	Items	M	SD	% of Variance	Loadings		Cronbach's Alpha
					EFA	CFA	
Leadership Style (LS)	LS1	2.97	0.996	23.536	0.842	0.848	0.847
	LS2	3.07	1.066		0.869	0.923	
	LS3	3.16	1.018		0.855	0.913	
	LS4	2.83	0.957		0.527	0.550	
Organizational Climate (OC)	OC1	3.38	0.925	18.365	0.830	0.808	0.839
	OC2	3.10	0.894		0.768	0.792	
	OC3	3.39	0.839		0.755	0.799	
	OC4	3.24	0.864		0.79	0.847	
Work style (WS)	WS1	2.95	0.891	16.334	0.662	0.837	0.899
	WS2	2.94	0.882		0.673	0.836	
	WS3	3.06	0.753		0.679	0.872	
	WS4	2.89	1.101		0.759	0.744	
	WS5	2.94	0.925		0.641	0.769	
Job satisfaction (JS)	JS3	3.55	1.787	7.252	0.631	0.663	0.718
	JS4	3.35	0.944		0.894	0.882	
Instrument Total	KMO			0.915			0.921
	p-value			0.000			

Note: Item details are as follows: LS1: Stability and sustainability of my current job. LS2: The supervisor-subordinate relationship in registration (civil) office. LS3: The professional ability of my supervisor in registration (civil) office. LS4: My current working condition in the registration (civil) office. OC1: The relationship between co-workers in my organization (registration office). OC2: Having a professional status if I continue working in this organization. OC3: My success and outcome is from my current work. OC4: The way my co-workers get along with each other. WS1: The freedom to use my own judgment. WS2: A chance to do something for my coworkers. WS3: A chance to do different things from time to time. WS4: The chances for advancement at my current job. WS5: Encouragement and praise from my supervisor for my good job performance. JS3: I'm satisfied with the contents of my job in general. JS4: I'm satisfied about the workload in general.

4.3. Confirmatory Factor Analysis (CFA)

After conducting EFA, researchers use CFA. According to the CFA, variables WS2, WS5, and LS4 are removed to get a better fit for the model. Consequently, goodness of fit of each model is evaluated and compared with the suggested criteria by the ratio of chi-square to degrees of freedom (χ^2/df), goodness-of-fit index (GFI), the adjusted goodness-of-fit index (AGFI), the root mean square error of approximation (RMSEA), and the comparative fit index (CFI). The measurement model of CFA in this model shows the fit index for the structural model, which indicated a good fit (χ^2/df = 1.342), RMSEA = 0.049, NFI = 0.895, CFI = 0.970, GFI = 0.903). Based on these statistics, the CFA model is accepted and the model is fit.

4.4. Composite Reliability, Convergent, and Discriminant Validity

Composite Reliability (CR), Convergent Validity, and Discriminant Validity are the extent to which indicators of a specific variable 'converge' or share a high proportion of variance in common. Convergent Validity includes two items: Composite Reliability (CR) and Average Variance Extracted (AVE). CR is a measure of reliability and internal consistency based on the square of the total of factor loadings for a construct [69]. AVE is a summary measure of convergence among a set of items representing a variable [70]. It is the average percent of variation explained among the items [69]. Anderson and Gerbing [69] suggest that the CR should be greater than 0.7 and Fornell and Larcker [70] suggest AVE to be at least 0.5. Table 2 summarizes the results of validity and reliability. The results provide the evidence supporting the reliability and validity of the indicators of the research model [71].

Table 2. Test of composite reliability, convergent validity, and discriminant validity.

	CR	AVE	MSV	Max r	JS	WS	LS	OC
JS	0.753	0.609	0.417	0.646	**0.780**			
WS	0.907	0.661	0.648	0.805	0.646	**0.813**		
LS	0.890	0.677	0.437	0.661	0.372	0.612	**0.823**	
OC	0.885	0.659	0.648	0.805	0.576	0.805	0.661	**0.812**

Note: CR > 0.7, AVE > 0.5, MSV < AVE, $\sqrt{AVE}$ > Max r, $\sqrt{AVE}$ is bold face diagonal.

4.5. Test of Hypotheses and Mediations

This study employs Structural Equation Modeling in order to test our proposed model and all the formulated hypotheses, which was discussed in Section 3. The results of the model fit for the structural model include the following values: $\chi^2/df = 1.113$ ($p > 0.05$), RMSEA = 0.028, NFI = 0.919, TLI = 0.989, CFI = 0.991, and GFI = 0.923. Table 3 recapitulates the results of hypotheses testing. Based on the results, three hypotheses are accepted (H1, H2, H3).

Table 3. Results of the hypotheses (standardized regression weights).

Hypothesis	Paths	Estimate	Statement of Hypothesis	Results
H1	LS → OC	0.622 ***	LS has a positive association with OC	Supported
H2	OC → WS	0. 812 ***	OC has a positive association with WS	Supported
H3	WS → JS	0.665 *	WS has a positive association with JS	Supported

* $p < 0.05$, *** $p < 0.001$.

Table 4 exhibits the result of the mediation hypotheses for the research model of this study. The results of mediation analysis, using 5000 resampling bootstrapping, support all mediation hypotheses (H4~H8) [72,73]. The following sections present meticulous discussion of the results shown in Tables 3 and 4.

Table 4. Results of the mediation hypotheses (standardized regression weights).

	Path	Indirect (ab)	Direct (c′)	Total (c)	Mediation
H4	LS → OC → JS	0.363 ***	0.016 (NS)	0.379 **	Supported
H5	LS → WS → JS	0.414 ***	0.035 (NS)	0.449 **	Supported
H6	LS → (OC & WS) → JS (Double Mediation)	0.378 ***	0.012 (NS)	0.390 *	Supported
H7	LS → OC → WS	0.475 ***	0.130 (NS)	0.605 **	Supported
H8	OC → WS → JS	0.441 *	0.128 (NS)	0.569 **	Supported

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5. Discussion and Managerial Implications

5.1. The Influence of Leadership Style (LS) on the Organizational Climate (OC)

Our findings exhibited in Table 3 accept H1 and conclude that LS has a positive association with OC. This important finding exhibits the positive and strong influence of LS on OC for register office employees in Mongolia. According to Jung et al. [25], a good organizational climate means a comfortable workplace. The leaders and managers of the organization create a content office. Consequently, the positive relationship between OC and LS is of utmost importance. Therefore, an effective leadership style can improve the organizational climate and, therefore, develop the organization's morale and upturn employee effectiveness.

This finding is also consistent with prior scholars' findings [27] emphasizing more support for the model with the Mongolian public register sector. The result shows strong ($\beta = 0.622$) and significant ($p < 0.001$) influence of leadership style on the organizational climate of the register sector. Therefore, H1 is accepted.

5.2. The Influence of Leadership Style (LS) on Job Satisfaction (JS) (Single Mediation of Organizational Climate and Mediation of Work Style)

H2 states that LS influences JS and hypothesizes that LS has a positive association with JS. The results of SEM analyses, however, indicate that, for the given model, the leadership style does not influence job satisfaction directly. H2 is, therefore, rejected. This result may not be consistent with some of the previous findings [49,52,53]. However, the previous studies did not take into consideration the mediation influences of the organizational climate (OC) and work style (WS). The proposed model of this study leads to a new discovery regarding the mediation of OC and WS (Table 4) as single separate mediators. Therefore, H4 and H5 are supported.

5.3. The Influence of the Leadership Style on Job Satisfaction (Serial Mediations of Organizational Climate and Work Style)

Hayes [74] illustrates serial multiple mediations with data from research conducted by Tal-Or et al. [75]. We showed that OC and WS as separate single mediators fully mediate the relationship between LS and JS. Furthermore, based on Hayes [74], we tested the serial multiple mediations of OC and WS. The result indicated full double mediation of OC and WS for the relationship between LS and JS (Table 4). Therefore, H6 is supported. This finding underscores the importance of OC and WS as the mediator between LS and JS.

5.4. The Influence of Leadership Style on Work Style and the Mediation of the Organizational Climate

H3 proposes that LS has a significant influence on OC. The structural model of this study rejects this hypothesis. Therefore, H3 is rejected. Furthermore, H10 states that OC is the mediator between LS and WS. The result of SEM analyses using the bootstrapping technique indicates that, for the given model, even though LS does not have a direct influence on WS, OC fully mediates the relationship between LS and WS. Therefore, H7 accepted.

5.5. The Influence of Organizational Climate (OC) on Work Style (WS)

H4 hypothesizes that OC has a positive association with WS. Niculiţă [33] indicates that "organizational climate factors such as positive motivation, positive interpersonal relationships, efficient management, and organizational support have proven to deliver positive influence on specific work style factors" (p. 1042). The results of current path analyses, which are shown in Table 3, indicate that OC significantly and positively influence WS ($\beta = 0.812$ and $p < 0.001$). H2 is, therefore, supported.

5.6. The influence of Organizational Climate (OC) on Job Satisfaction (JS) and the Mediation of Work Style (WS)

H5 hypothesizes that OC has a positive association with JS. Several previous studies [41,65,66] have obtained the positive and significant relationship between the organizational climate and job satisfaction. However, the results of the path analyses indicate (Table 3) that, with the presence of work style, there is no significant influence of OC on JS. H5 is, therefore, rejected.

The finding, however, leads to another more important discovery regarding the mediation effect of work style, which was proposed by the new model (Table 4). WS fully mediates the influence of OC on JS. Thus, H11 is accepted. A good organizational climate requires a fair and clear policy, clear information, and an effective leader. Although the finding is not consistent with previous studies regarding the direct effect of OC on JS, this study introduces the significant mediating role of WS.

5.7. The Influence of Work Style (WS) on Job Satisfaction (JS)

H6 states that WS has a positive association with JS. Many studies [31,43–48,76] have acquired the positive and significant relationship between work style and job satisfaction. The result of this study ($\beta = 0.665$, $p < 0.001$) is consistent with a previous study and, consequently, H3 is accepted.

5.8. Discussion

In recent years, numerous scholars have been studying the relationship between employees' job satisfaction (JS) and respective factors such as leadership style (LS), organizational climate (OC), and work style (WS). However, very few papers have considered the above issue in the public sector. In addition, previous studies only found a direct and positive effect on employees' job satisfaction (JS) but ignored the mediating effects. This is one of the most important issues for human resource management because this could help improve employees' job satisfaction if we know its relationship with LS, OC, and WS. Our goal is to identify the factors influencing employees' job satisfaction. Furthermore, this study proposes a new model not only to test the direct effects but also the mediating effects on employees' job satisfaction. Thus, this paper bridges the gap of the literature to study the issue using Mongolian register office employees.

Previous studies have shown the importance of LS on JS and employee turnover. The proposed model of this study illustrates the importance of OC and WS in the relationship between the LS and JS. Leadership is one of the main factors for success in any kind of group activities. The workers-leader relationship is a key factor that influences workers' satisfaction in the workplace. However, what about employees' perceptions about organizational features like decision-making and rule setting in the workplace? The organizational climate is specific for each group and one leadership style will not fit all climates. Leaders need to rely on a positive climate in their workplace to enhance employee motivation and satisfaction. The proposed model of this study gives strong evidence for the important role of the organizational climate in order to increase job satisfaction.

Likewise, the harmony and accord of individual's professional activities and moral qualities are essential to one's satisfaction in life and work. Working style is stable and trait-like attributes of an employee. An individual's work style is developed in childhood through experimentation and reinforcement and then crystallized in adulthood. Leaders should pay attention to an individual's work style to develop sustainable and higher job satisfaction. The direct effect of LS on JS was studied. However, the results of this study introduce the intermediary role of WS on JS. Thus, when LS is combined with OC, WS will result in sustainable and higher JS.

Providing the right leadership is the key element in employee job satisfaction. However, the leaders should also take into consideration the organizational climate as well as employees' work style. In organizations with skillful employees and a good leadership style, a proper organizational climate and consideration for employees' work style would further influence job satisfaction and can improve employee retention.

Findings of this study contribute to research on job satisfaction by delineating several combinations of antecedents that influence employees' job satisfaction in order to register the organization of Mongolia. For employees, working in public sector organizations may require effort to improve his/her moral and attention for the advancement of high productivity. Nevertheless, working in a positive organizational climate and identifying with a suitable leadership style can improve job satisfaction in register offices. Thus, when officers of the register office create a positive organizational climate through positive interaction as well as an appropriate leadership style to match employees' work style, employees' job satisfaction will be high. Leadership style will help job satisfaction, but sustainability of job satisfaction relies on the organizational climate and the work style of employees. When leaders of an organization implement employee's work style into their leadership style, job satisfaction increases. The suitable organizational climate will also influence employees' work style. The combination of the organizational climate and work style implemented properly into the leadership style would improve the sustainability of the job satisfaction level.

5.9. Managerial Implications

The results of current research show that respective factors are important to study employees' job satisfaction. Managers can use the results to improve planning of the human resource strategy and implement their leadership style more effectively. The results also suggested that not only effective leadership style is required in this sector. The mediating role of the organizational climate and work style should not be ignored. Furthermore, by using the proposed research model, this research can be expanded to other public sector organizations employees' job satisfaction.

A good understanding of the mediating role of work style and organizational climate would improve the influence of leadership style on job satisfaction. Our research provides guidance for Mongolian public office managers who wonder what they should do to improve job satisfaction. The findings of this study will be utilized for the managerial practice and improvement of human resource policy.

6. Conclusions

This study bases itself on the traditional variables relating to job satisfaction with the new model to suggest mediating variables that can help sustain employees' satisfaction. Furthermore, Mongolia as one of the emerging economies seldom has been the topic of various studies. Findings of this study paves the road to research on job satisfaction by outlining traditional antecedents that influence employees' job satisfaction and integrating them into a new model. This is the first study to investigate the relationship between leadership style and job satisfaction with Mongolian public sector employees. The main emphasis of this paper is to show the importance of the mediators. The findings of this study reconfirm the previous studies' outcomes that are associated with the positive influence of leadership style on the organizational climate. Likewise, the positive and significant influence of organizational climate on work style is tested and confirmed. Furthermore, we established and reconfirmed the positive significant influence of work style on job satisfaction.

The first three hypotheses were to show and reconfirm the external validity of the study. The next five hypotheses introduced in this model bring new discoveries and reiterate the importance of work style and organizational climate as the mediating variables. The role of the mediating variables is to improve sustainability of the relationship between leadership style and job satisfaction. The organizational climate is a significant mediator that fully binds and helps sustain the relationship between leadership style and job satisfaction. The same is true for work style. The organizational climate and work style combination, as the mediators helping the sustainability of the relationship between leadership style and job satisfaction, is also tested and the results show strong significant full mediation. The organizational climate fully mediates the relationship between leadership style and work style. Therefore, leaders can create a more sustainable work style by improving the organization's climate. This study signposts the importance of work style in sustaining the relationship between the organizational climate and job satisfaction. The organizational climate can sustainably influence employees' job satisfaction if the work style of each individual employee is respected and taken into account.

This paper studies sustainability of leadership and satisfied employees for the organizational climate and work style. An extension of our paper could study sustainability of leadership and satisfied employees for other variables. Further research could also study sustainability for other issues. For example, extending Mou et al. [77] and others to study the sustainability for enterprise supply chains, extend Li et al. [78] and others to study the sustainability of portfolio selection, extend Tsendsuren et al. [79] and others to study the sustainability of life insurance, extend Wong, et al. [80] to study the sustainability of warrant markets, extend Liao and Wong [81], Liao et al. [82], Purevdulam et al. [83], Moslehpour et al. [71] to study the sustainability of e-shopping, extend Pham et al. [84] to study the sustainability of outsourcing business, and extend Moslehpour et al. [85,86] to study the sustainability of marketing. This study is limited to public employees of the Mongolian public sector in Ulaanbaatar. However, the capital of Ulaanbaatar has 9 districts and 152 primary units of registration office. Future studies need to study the private sector employees in Mongolia and look at the differences if there are any.

The Government of Mongolia, as one of the emerging economies of the world, strives to implement appropriate human resource strategy to satisfy and retain government employees. There is an inevitable need for the sustainability of leadership and satisfied employees. Mongolian government organizations can benefit from empirical studies to implement a good human resource strategy. This study provides an opportunity to establish the fundamental basis by providing the grounds for future studies in this area. In practice, leaders and supervisors should pay attention to which factors are the most important and influential in the current transitional situation of Mongolia. Especially, as discussed in this study, factors such as organizational climate and work style are essential for the sustainability of the path between leadership style and employee satisfaction. Therefore, they must focus on human research management in theory and practice.

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An Analysis of Gains to US Acquiring REIT Shareholders in Domestic and Cross-Border Mergers before and after the Subprime Mortgage Crisis

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Abstract: This paper examines the abnormal returns of acquiring real estate investment trusts (REITs) around the announcement of acquisitions before and after the subprime mortgage crisis. Based on 182 domestic and cross-border US REIT acquisition announcements from 2005 to 2010, the acquiring trusts experienced a 0.73% abnormal return, on average. When the sample was divided into pre-crisis, crisis, and after-crisis subsamples, the acquiring trusts enjoyed the largest abnormal returns (1.86%) for domestic acquisitions during the crisis period. Before the crisis, when the acquisition was cross-border, the target was private, or the transaction was cash-financed, the acquiring trust experienced larger abnormal returns. During the crisis period, the acquiring trust gained larger abnormal returns when the transaction value was larger. After the crisis period, the acquiring trust achieved less abnormal returns in cross-border mergers. For both pre- and after-crisis periods, the shareholders of the acquirer enjoyed larger abnormal returns when the mergers were cash-financed, regardless of whether the target was public or privately held. Neither the blockholder monitoring nor the signaling hypothesis can explain such value gains. The structural changes in the acquirer's abnormal returns are possibly due to the increased risk aversion of the market participants following the crisis.

Keywords: merger; subprime mortgage crisis; event study

1. Introduction

In the early period of the 2000s, the U.S. was experiencing mild economic growth and rising housing prices when the interest rates were low. Because of the rising home prices later on, bankers were encouraged to make more loans for higher compensations, and the quality of the mortgage loans started to deteriorate, especially when the mortgage rates started to rise. The first disruption of the credit market can be dated back to 7 August 2007, when the French bank BNP Paribas suspended the redemption of the shares held in some of its money market funds [1]. Furthermore, on 15 September 2018, the investment bank Lehman Brothers filed for the largest bankruptcy in U.S. history due to its loss during the subprime mortgage market. Reinhart and Rogoff [2] stated that the aftermath of the crisis has three characteristics: the asset market collapses are prolonged, the banking crisis is associated with profound declines in output and employment, and the level of government debt tends to explode. The outbreak of the global financial crisis in 2008 has reshaped the landscape of the financial markets as well. Investors have become more risk-averse, and that has changed the corporate strategies in business activities. It is important to examine how corporations have adjusted their mergers and acquisitions strategies since the crisis and to explore how market participants perceive the acquisition activities. To keep corporations sustainable, acquirers must identify the right targets from long-term perspectives. For example, are the prices of the targets appropriate during the normal periods or the crisis periods? Will the acquisitions help the corporations grow? If the acquisitions are favorable, the market participants will revalue the acquirer's stock price.

Acquisitions may benefit shareholders from different sources, such as revenue enhancement from marketing gains and market monopoly power, cost reductions from economies of scale and the elimination of inefficient management, tax gains, and a reduced cost of capital. The wealth effect of the acquisition has been well documented in the corporate finance literature. A stylized fact concerning mergers is that the shareholders of bidding firms suffer wealth loss at the announcement of stock-financed merger transactions. This is consistent with the information asymmetry hypothesis, in which the manager considers the firm's stocks overvalued, and stock instead of cash is chosen as the payment method for a merger transaction. Jensen and Ruback [3] reported the short-run evidence from studies that used event studies and looked at the effect of a merger announcement on abnormal stock returns. The abnormal returns associated with successful corporate takeover bids for the target firms are 30%, 20%, and 8% in the cases of a tender offer, merger, and proxy contest, respectively. However, for the bidding firms, the abnormal returns are much smaller or close to zero.

On the other hand, other corporate finance literature has documented the opposite results for the acquirer's abnormal returns. For example, Asquith et al. [4] concluded that bidding firms gain during the 21 days before the announcements of merger bids. Bidders' abnormal returns are positively related to the relative size of the merger partners, and the gains around the announcement period are larger for successful mergers. They concluded that their findings are consistent with the value-maximization behavior of the management of the bidding firms. The inconclusive results documented in earlier studies for the gains or losses of bidding firms around the merger announcement are partially explained by the relative size of the merger partner and the time period of the merger.

The purpose of this study is to reexamine the effects of real estate investment trust (REIT) acquisitions on the wealth of the shareholders of the acquiring trust before and after the subprime mortgage crisis. REITs allow investors to indirectly invest in professionally managed commercial real estate portfolios and then distribute rents and capital gains to their investors. REITs have unique institutional settings characterized by very codified and transparent corporate governance. Since REITs do not normally pay federal income taxes and are required to distribute at least 90% of their taxable income, they are highly dependent on their ability to access external capital. Thus, REITs are especially vulnerable during a credit crisis [5]. There are several advantages for a REIT to acquire another trust. For example, net operating losses can be used to offset capital gains tax liabilities from the sale of trust property, making an existing trust an attractive target. Furthermore, the merger may replace existing inefficient management in the acquired trust and result in better utilization of assets (see Allen and Sirmans [6] for detailed descriptions of the institutional background of REITs).

The gains to the bidders from mergers when both the buyer and seller are REITs have also been examined in previous studies. The short-run evidence from the studies using event studies and looking at the effects of mergers on abnormal stock returns for REITs is also inconclusive. For example, with a sample of REIT mergers over the period of 1977–1983, Allen and Sirmans [6] concluded that REIT acquisitions significantly increased the wealth of the acquirer's shareholders, and they argued that the value gain comes from the improved management of the acquired trusts' assets, rather than the tax benefits.

Campbell et al. [7] examined the information content of the method of payment in REIT mergers from 1994 to 1998. They documented that, when the target firm is publicly held, the transactions are always stock-financed, and the acquiring firm's shareholders sustain small negative returns around the announcement date. The explanation for the negative returns is that the acquirer's stock is overvalued. When the target is privately held, the acquirer returns are positive in stock-financed mergers. Their finding may be explained by two hypotheses: the blockholder monitoring hypothesis and the signaling hypothesis. Chang [8] argued that this value enhancement may be caused by the monitoring benefits provided by new blockholders often observed in public-private mergers (blockholder monitoring hypothesis). Alternatively, the owners of private targets are also expected to be better informed about the prospects of the acquiring firm, and their willingness to hold the acquirer's stock provides a positive signal to the market (signaling hypothesis). Campbell et al. [7] concluded that the information signaling hypothesis is the dominant explanation. Sahin [9] examined the performance of acquisitions in the REIT industry from 1994 to 1998. The results indicated that the acquiring REITs suffer statistically significant negative abnormal returns, while the target REITs earn statistically significant positive returns around the announcement date.

To further explore the wealth effect of REIT mergers on the acquiring trust, this study examines the short-run performance of the acquirer in 182 REIT mergers around the announcement dates in the period of 2005Q4–2010Q4 from the perspectives of domestic versus cross-border mergers. Unlike the previous studies, our sample period spans the subprime mortgage crisis period, and we try to highlight the importance of the change in the risk appetite of market participants due to the subprime mortgage crisis by distinguishing domestic from cross-border mergers.

Unlike previous REIT merger literature, there are considerably more REIT merger events in our sample. By considering domestic and cross-border REIT merger announcements over different subperiods, we found that the shareholders of the acquirer achieved significant value gains from cross-border mergers during the crisis period only. The gain is attributable to the lower stock prices of the target trusts. From a cross-sectional analysis, we found that, before the crisis period, if the merger was cross-border, the target trust was privately held, or the merger was cash-financed, the acquirer achieved larger abnormal returns. During the crisis period, a larger acquisition value was associated with a larger value gain to the acquirer. This finding reinforces the hypothesis that the gains come from the undervalued assets of the target REITs during the crisis period. Following the onset of the subprime mortgage crisis, the acquirer achieved more value gain when the target was domestic (rather than cross-border), the acquisition was cash-financed, or there were more states in which the acquirer had properties. This evidence suggests that investors increased their degree of risk aversion after the subprime mortgage crisis because cross-border acquisitions are associated with higher risk resulting from corporate governance, cultural differences, information asymmetries, and valuation issues. If the acquirer has properties in more states, the acquirer's sources of future cash flows are more geographically diversified. The remainder of this paper is organized as follows. Section 2 reviews the literature concerning the wealth effect in merger transactions. The data and research methodology are detailed in Section 3. An empirical analysis is given in Section 4. The final section concludes this paper.

2. Literature Review

2.1. Cross-Border Mergers

Internationalization theory suggests that cross-border acquisitions result in gains from diversification when a business seeks synergies from intangible assets, such as information-based assets [10,11]. Quah and Young [12] asserted that the management of both cultural and organizational integrations in cross-border mergers will tend to make acquisitions successful, but poor attention to these issues will destroy synergistic gains. Cross-border mergers are affected by factors such as cultural identity, physical distance, corporate governance, and equity market valuation differences [13]. In terms of valuation differences, if the difference is temporary, the cross-border acquisitions effectively arbitrage these differences. The valuation difference can also be permanent. Kindleberger [14] argued that cross-border acquisitions can occur because the expected earnings are larger or the cost of capital is lower. For example, if a firm is involved in overseas sales or imports, the firm can acquire a foreign target when the target currency depreciates.

With a sample of 4430 corporate acquisitions for the period of 1985–1995, Moeller and Schlingemann [15] found that US firms who acquire cross-border targets relative to those that acquire domestic targets suffer significantly lower announcement stock returns of approximately 1%. Moeller and Schlingemann [15] summarized several disadvantages of market integration, including increases in competition in the market for corporate control, increases in hubris and agency problems, the cost of internalization, and a decrease in value from diversification.

Other evidence of bidders' abnormal stock returns in cross-border merger announcements is, however, mixed. Dutta et al. [16] found that bidders in the United States had positive cumulative abnormal returns in cross-border mergers. Martynova and Renneboog [17] documented that acquirers engaging in cross-border bids experienced fewer announcement effects than those associated with domestic acquisitions (0.4% and 0.6%, respectively). However, Aybar and Ficici [18] and Chakrabarti et al. [19] found negative cumulative abnormal returns.

2.2. REIT Mergers

Allen and Sirmans [6] conducted the first study concerning the wealth effects of REIT mergers by examining 38 successful REIT–REIT mergers from 1977 to 1983. They found significant positive abnormal returns for the acquirers, which is in contrast to the small negative return from corporate deals. Extending the research of Allen and Sirmans [6], McIntosh et al. [20] examined the return for 27 target REITs over the period of 1962–1986, finding a positive and significant average abnormal return of 2.16%. They concluded that the results are consistent with the hypothesis that target REITs achieve a positive wealth effect due to a merger announcement.

With a REIT merger sample over the period of 1994–1998, Campbell et al. [7] found that, when the target REIT was public, the transactions were always stock-financed, and the shareholders of the acquiring REITs suffered negative returns around the announcement. When the target REIT was privately held, cash financing, mixed financing, and the placement of the acquirer's stock with target owners were more prevalent. Acquirer shareholders achieved positive abnormal returns around the announcement of stock-financed mergers when the target was private, which is consistent with the monitoring by blockholders hypothesis and information signaling hypothesis. Sahin [9] also examined the performance of acquisitions in the REIT industry around the acquisition announcement. The results indicated that the acquiring REITs suffered statistically significant negative abnormal returns. This finding is in line with the research by Campbell et al. [7] but inconsistent with the finding of Allen and Sirmans [6]. The difference is argued to be due to the different environments in the 1980s and 1990s.

Ooi, Ong, and Neo [21] investigated 228 merger announcements in the Japanese and Singaporean REIT markets from 2002 to 2007, suggesting that aggressive growth acquisitions by Asian REITs were a result of improved economies of scale and better management practices. Their results showed that the bidding REITs earned positive and significant abnormal returns of 0.21%. Finally, Ling, and Petrova [22] examined the wealth effects of public-public and public-private REIT merger announcements from 1994 to 2007 and found that targets in public-private mergers earned higher abnormal returns than those in public-public announcements (cumulative abnormal returns were 10.38% and 7.7%, respectively).

2.3. Mergers in the Subprime Mortgage Crisis

Numerous studies examined the wealth effects of mergers during the subprime mortgage crisis period. Berger and Bouwman [23] indicated that healthy banks, particularly from the point of view of capital and liquidity, have an opportunity to improve their market share and profitability during a crisis by making acquisitions. Thus, this implies positive abnormal returns because acquirers can acquire other banks at lower prices and also benefit from portfolio diversification [24] and market power [25]. Furthermore, Reddy et al. [26] examined 26 countries' cross-border mergers from 2004 to 2010 and found that, following the onset of the crisis, companies in emerging countries took advantage of attractive asset prices by acquiring firms in developed countries. Beltratti and Paladino [27] also showed that investors attached significant uncertainty to the completion of deals and rewarded successful acquisitions with delayed abnormal returns during the crisis period.

3. Data and Methodology

3.1. Data

The sample consists of 182 merger announcements made by 229 publicly traded REITs on NYSE between 2005Q4 and 2010Q4. The data were collected from SDC Platinum and Datastream. Of the 182 merger announcements, there are 106 cash-financed, 4 stock-financed, and 10 hybrid transactions. For the rest of the transactions, they are indicated as "unknown" in SDC Platinum.

The 182 transaction announcements have a total value equivalent to 22062.59 million dollars. Table 1 illustrates the distribution of the number of REIT merger announcements for each year. Table 2 shows the compositions of REIT merger announcements for domestic and cross-border transactions before the subprime mortgage crisis period (2005Q4–2007Q1), during the subprime mortgage crisis period (2007Q2–2009Q1), and after the subprime mortgage crisis period (2009Q2–2010Q4).

Table 1. Number of acquisitions from 2005 to 2010 and corresponding transaction value.

Year	Total Number of Acquisitions	Total Transaction Value (US$ million)
2005	17	$1817.22
2006	39	$5165.38
2007	35	$8817.75
2008	30	$2201.90
2009	16	$445.74
2010	45	$3614.60
Total	182	$2,2062.59

Table 2. Profile of domestic and cross-border mergers and acquisitions (M&A) announcements made before, during and after the subprime mortgage crisis.

	Before the Crisis (1 October 2005–31 March 2007)	During the Crisis (1 April 2007–31 March 2009)	After the Crisis (1 April 2009–31 December 2010)
Number (%) of domestic M&A	56 (35%)	54 (34%)	50 (31%)
Number (%) of cross-border M&A	9 (41%)	7 (32%)	6 (27%)

3.2. Methodology

3.2.1. Measuring Abnormal Returns

This study followed the standard event study methodology of Brown and Warner [28,29] to analyze the effect of the merger announcement on REIT acquirers' stock price returns. We followed the market model approach to assume a linear relationship between the expected return on a security and the return on the market portfolio. Specifically, for each security i, the market model assumes the return on security, given by:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}, \tag{1}$$

where R_{it} is the return on security i at time t. R_{mt} is the return on the market portfolio at period t. The linearity and normality of returns are assumed, and ε_{it} is the error. α_i and β_i are coefficients. The market model expressed in Equation (1) is used to compute the expected return on the stock on the day of the event or during a selected event window. Equation (1) is first estimated with the sample observed during the 89-day estimation window from $t = -94$ to $t = -6$, where $t = 0$ is the event day.

The abnormal return (*AR*) due to the announcement on any given day, therefore, equals the actual return minus the predicted normal return:

$$AR_{it} = R_{it} - (\alpha_i + \beta_i R_{mt}). \tag{2}$$

To obtain a general insight into the abnormal return observations for a sample of *N* firms, the average abnormal returns (*AAR*) for each day *t* are averaged as follows:

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{it}. \tag{3}$$

The event window is the period between τ days prior to the event and τ days after the event. The expected returns on the stock calculated from Equation (1) for the security during the event window ($-\tau$, $+\tau$) are compared with the actual returns on each day in the event window. The cumulative difference between the predicted return and the actual return in the event window is called the cumulative abnormal return and is calculated as follows:

$$CAR_i(-\tau,\ +\tau) = \sum_{t=-\tau}^{+\tau} AR_{it} \tag{4}$$

The last step is to calculate the *t*-value. First, the standard deviation *(S)* is calculated as follows:

$$S\ = \sqrt{\frac{\sum_{i=1}^{N}(CAR_i - CAAR_i)^2}{N-1}}, \tag{5}$$

where $CAAR_i$ is the average value of CAR_i, and *N* is the total number of firms. Then, the *t*-value is calculated as follows:

$$t\ = \frac{CAAR_i - 0}{S/\sqrt{N}}, \tag{6}$$

where *N* is the total number of firms.

3.2.2. Cross-Sectional Regression Models

A cross-sectional regression was applied to identify the sources of cumulative abnormal returns from merger announcements. The dependent variable is the 2-day *CAR* (0, +1) for all regression models. The independent variables in the regression models are listed and illustrated in Table 3.

Table 3. Definition and summary statistics for the explanatory variables.

Variable	Definition	Mean	Std dev.
DOMES	Type dummy, equals one for domestic M&A and zero otherwise.	0.87	0.34
CRISIS	Subprime dummy, equals one for M&As made during 2007Q2 and 2009Q1, and zero otherwise.	0.33	0.47
*DOMES*CRISIS*	Interacting dummy, equals one for domestic M&As made during subprime and zero otherwise.	0.29	0.45
STATUS	Target public status dummy, equals one for privately held and zero otherwise.	0.66	0.47
STRUCTURE	Method of payment dummy, equals one for all cash-financed and zero otherwise.	0.44	0.50
R_SIZE	Deal value divided by market capitalization of acquirers.	0.09	0.22
ROE	Return of equity from acquirers.	0.08	0.13
EQUITY	Equity divided by total assets from acquirers.	0.38	0.18
STATES	The number of states that the REITs firm has properties in.	13.84	11.07

182 domestic and cross-border REITs M&A announcements from October 2005 to December 2010.

The major independent variable is domestic merger (*DOMES*), which is a dummy variable equaling one for a domestic merger and zero otherwise. If the cross-border merger announcements consist of additional information, the coefficient of *DOMES* is expected to be statistically significant. The regression models control for the other acquisition attributes: public or private target (*STATUS*), payment structure (*STRUCTURE*), size of the transaction relative to the acquiring REIT (*R_SIZE*), return on equity of the acquiring REIT (*ROE*), the ratio of equity to total assets (*EQUITY*), and the number of states in which the acquiring REIT has properties (*STATES)*.

STATUS equals one if the target REIT is privately held and zero if it is publicly held. It is expected to positively influence the abnormal return because privately held firms are frequently controlled by fewer investors who are easier to negotiate with than those in publicly held firms [30]. Also, in the corporate finance literature, Chang [8] concluded that the acquirer achieves positive abnormal returns in the announcement period of public-private mergers when the transaction is stock-financed. The wealth gain is argued to come from the monitoring by blockholders and the reduced information asymmetry.

STRUCTURE is also a dummy variable that controls for the method of payment of merger deals. *STRUCTURE* equals one if the merger deal is cash-financed and zero otherwise. It is expected to positively influence the abnormal return because acquirers prefer a cash payment when their stock is undervalued [31]. Previous studies, such as Campbell et al. [7], concluded that the acquiring REIT achieves positive abnormal returns during the announcement period in public-private mergers when the transaction is stock-financed. Although our data do not contain information on whether the merger transaction was stock-financed, we incorporated the cross-product term, $STATUS \times STRUCTURE$, to examine whether the acquirer will experience a positive or negative effect in a cash-financed merger transaction when the target REIT is private. *R_SIZE* is the relative value of both the target and acquiring firms. It is expected to positively influence the abnormal return due to the value-maximizing behavior exhibited by the management of bidding firms [4].

The variable *ROE* measures the acquirers' profitability and is expected to positively affect the abnormal returns, because the bidding firms with better profitability are better equipped to restructure the target firms [27]. *EQUITY* measures the capital strength of acquirers and is expected to have a positive influence because more leveraged firms are susceptible to a greater degree of investor sentiment [32].

STATES is a proxy variable of geographic diversification. Geringer et al. [33] considered the ratio of a company's foreign subsidiaries' sales to its total worldwide sales as the internationalization variable. Kim et al. [34] measured the degree of global diversification by the number of employees in foreign countries. Due to the characteristics of REIT firms having properties in states other than their asset portfolio, the number of states in which a REIT has properties was used as a proxy for the degree of geographic diversification. The cross-sectional regression model of the 2-day CAR is characterized as follows:

$$\begin{aligned} CAR\ (0,+1) = {} & \beta_0 + \beta_1 DOMES + \beta_2\ STATUS + \beta_3 STRUCTURE \\ & + \beta_4 STATUS \times STRUCTURE + \beta_5 R_{SIZE} + \beta_6 ROE \\ & + \beta_7 EQUITY + \beta_8 STATES + \varepsilon \end{aligned} \tag{7}$$

4. Empirical Results

4.1. Abnormal Returns of the Acquiring REITs in Domestic and Cross-Border Merger Announcements

Table 4 shows the *CAAR* around the merger announcements. *CAAR*s are reported for the three different event windows: *CAAR* (−1, 1), *CAAR* (0, 1), and *CAAR* (0, 2). Overall, the average return from all merger announcements was 0.8% surrounding a 3-day window (from day 0 to + 2) and 0.73% between day 0 and 1.

Our results are consistent with Allen and Sirmans [6], in which the acquirer had a positive abnormal return around the merger announcement. Campbell et al. [35] also found positive excess return for REIT bidders for the 3-day announcement period following public-private mergers. Overall, our findings support previous evidence in the real estate literature that indicate that bidding firms enjoy more excess in their returns in mergers compared with findings from general corporate finance literature.

Table 4. Cumulative average abnormal returns for the acquiring trusts in REIT merger announcements.

Day/window	Domestic M&A	Cross-Border M&A	All M&A Announcements
CAAR (−1,1)	0.67%**	0.21%	0.61%**
CAAR (0,1)	0.78%**	0.41%	0.73%**
CAAR (0,2)	0.82%*	0.66%	0.80%**
Obs.	160	22	182

** and * indicate significant at 5% and 10% significance levels, respectively. *CAAR* denotes the average value of the cumulative abnormal return (*CAR*).

Table 5 shows the mean cumulative abnormal returns for the acquiring trusts in domestic and cross-border REIT merger announcements from day 0 to day 1, *CAAR* (0, 1), during the three subperiods: before-the-crisis, during-the-crisis, and after-the-crisis periods. Only the *CAAR* for domestic merger announcements during the crisis period is positive and significant. Our results contrast with those reported by Amewu [36] and Beltratti and Paladino [27], who concluded that there was no significant change in abnormal returns on bidding firms' shares following the onset of the global financial crisis. The reason for the positive and significant abnormal returns for the acquiring REITs could be the value gains from investing in the distressed stock price of the target REITs during the crisis period.

The short-term wealth effects of the acquirers around the announcements of the domestic and cross-border mergers have also been documented in the corporate finance literature. Moeller and Schlingemann [15] provided evidence that U.S. firms who acquire cross-border targets relative to those that acquire domestic targets experience significantly lower announcement stock returns of approximately 1%. Acquirers' stock returns are negatively associated with global and industrial diversification. They concluded that the bidder return is positively associated with the legal system favoring strong shareholder rights and negatively associated with restrictive target countries. Mateev and Andonov [37] also found that bidding firms engaging in cross-border bids suffer lower announcement effects than those undertaking domestic acquisitions. They also provided evidence that cross-border bidding firms tend to suffer lower returns when the targets are located in countries with stronger investor protection mechanisms.

Furthermore, Table 5 shows that the average acquirers' *CAAR* was larger for cross-border merger announcements than that for domestic merger announcements before the crisis period, although neither is significant. During the crisis period, acquirers' *CAAR* was positive and statistically significant for domestic merger announcements only. In the aftermath of the crisis period, the acquirers' *CAAR* became smaller and insignificant for domestic mergers and negative for cross-border mergers, although neither is statistically significant.

We can summarize the findings for the short-term wealth effect of the REIT acquirers as follows. First, the acquirers achieved higher returns for domestic mergers than cross-border mergers. Acquirers realize a lower wealth effect from cross-border mergers. This is consistent with the argument in the literature that when the targets are in countries with more economic restrictions, such as investor protection mechanisms, which is likely true in general when compared with the U.S., the U.S. acquirers suffer lower returns than the returns in the case of domestic mergers. Second, acquirers achieved positive and statistically significant abnormal returns during the crisis period only. The gains in wealth were mainly from the distressed prices of the targets.

Table 5. Cumulative average abnormal returns for domestic and cross-border merger announcements during subperiods.

	Before the Crisis		**During the Crisis**		**After the Crisis**	
	CAAR(0,1)	*t*-stats	*CAAR*(0,1)	*t*-stats	*CAAR*(0,1)	*t*-stats
Domestic	0.13%	0.43	1.86%	2.89 ***	0.34%	0.55
Cross-border	0.58%	1.47	1.28%	0.62	−0.83%	−0.85
All	0.19%	0.71	1.79%	2.92 ***	0.21%	0.37

*** indicates significant at 1% significance level.

4.2. Cross-Sectional Analysis of Abnormal Returns

Table 6 shows the results of the regressions of *CAR* from day 0 to day 1 for the acquiring firm during the three subperiods: before the crisis, during the crisis, and after the crisis, respectively. Before the crisis, when the target was domestic, the acquiring REIT achieved lower announcement returns than when the target was cross-border. This is consistent with the finding in Sahin [9] and with the internationalization theory, in which gains are from diversification when businesses seek synergies from intangible assets, such as information-based assets [10,11].

Second, the *CAR* of the acquiring REIT was larger when the target firm was private and when the merger transaction was cash-financed. Campbell et al. [7] concluded that acquirer returns were positive in stock-financed mergers when the target is private. Our results indicate that when the merger was cash-financed, the acquirer returns were positive, regardless of the public or private status of the target. This can be explained by the undervalued stocks of the acquiring REITs [31]. This finding—that when the target was private, the acquirer announcement returns were positive regardless of the method of payment—needs to be explained. In the corporate finance literature, Chang [8] concluded the acquirer achieves positive abnormal returns in the announcement period of public-private mergers when the transaction is stock-financed. He concluded that the wealth gain comes from the monitoring by blockholders and the reduction in information asymmetry. Campbell et al. [7] argued that the acquiring REIT valuation gain from the merger announcement when the target is private is better explained by the signaling effect.

However, the signaling effect cannot explain why the acquirer achieves a positive wealth effect from the merger announcement when the merger transaction is not stock-financed. For corporate acquisitions, Conn et al. [30] concluded that both domestic and cross-border private acquisitions result in positive announcement returns. They discussed several potential explanations for positive acquisition announcement returns when the target is private. For example, the process of making private bids is less exposed to the public gaze, and the acquirer can end the negotiation without loss of face. Poor acquisition outcomes due to hubris are less likely when the target is private. Also, the stocks of the private target are at a discount because of the illiquidity and other trading frictions. When the public acquirer purchases the assets of the private target, the potential value gain of the private target can be realized by the management of the public acquirer.

Finally, the size of the merger relative to the capitalization of the acquiring firm was marginally negatively associated with *CAR*, which contradicts our expectation. When we incorporate the interaction term of *STATUS* and *R_SIZE*, the coefficient of *R_SIZE* remains negative but becomes insignificant. The coefficient of the above interaction term is positive but, again, is insignificant (to save space, it is not reported in Table 6).

During the crisis period, only the size of the merger transaction relative to the capitalization of the acquiring firm was positively associated with the *CAR*. This finding is consistent with the finding in Table 5, in which the reason for the positive and significant abnormal returns for the acquiring firms could be the value gains from investing in the undervalued stocks of the target REITs during the crisis period. This is supported by the argument of Reddy et al. [26]. As the deal size becomes larger, the gains from the merger for the acquiring firm become larger.

During the after-crisis period, the acquiring firms' *CAR* was larger when the target was domestic compared with the cross-border target. This reverses the finding from the pre-crisis period, but this is consistent with the finding of Conn et al. [30], who concluded that both the announcement and long-run returns of cross-border mergers are lower than those of domestic mergers. That is, before the crisis, synergies from international diversification dominates the effects of the aforementioned cross-border cultural differences, corporate governance, and valuation differences. However, following the crisis, the latter effects dominate the synergies from international diversification. This may suggest that since market participants became more risk-averse after the onset of the crisis, the market reacted to cross-border merger announcements less favorably than domestic mergers due to uncertainty and information asymmetries.

Furthermore, unlike the case for the pre-crisis period, when the target firm was private, the *CAR* became smaller, although it was not statistically significant. This corresponds to the increase in risk aversion of the market participants following the onset of the crisis: private target firms had more information asymmetry, and the stock prices of the acquiring REITs reacted to the merger announcement less favorably.

In the after-crisis period, when the acquisition was cash-financed, like the case for the pre-crisis period, the *CAR* was larger than that for other methods of payment. Finally, the number of states in which the acquirer had properties also positively affected the acquirer's *CAR*. This again corresponds to the argument of the increase in market participants' risk aversion. If the acquirer's properties had more geographic diversification, the acquirer's announcement return was higher. This effect of the number of states in which the acquirer has properties had no effect on the acquirer's merger announcement return before the crisis or during the crisis periods.

Table 6. Cross-sectional analysis: regressions of cumulative abnormal returns from day 0 to day 1.

Independent Variable	Before the Crisis	During the Crisis	After the Crisis
DOMES	−0.0109 (−1.44)	0.0158 (0.82)	0.0426 ** (2.11)
STATUS	0.0145 ** (2.22)	−0.01687 (−1.20)	−0.0283 ** (−2.00)
STRUCTURE	0.0092 * (1.66)	−0.01221 (−0.80)	0.0215 * (1.83)
R_SIZE	−0.0124 * (−1.79)	0.2101 ** (2.44)	−0.0238 (−0.44)
ROE	0.0246 (1.17)	−0.0436 (−1.14)	−0.0566 (−0.89)
STATES	-1.2×10^{-5} (−0.05)	−0.0005 (−0.96)	0.0011 * (1.91)
Constant	−0.0124 (−1.19)	−0.0051 (−0.20)	−0.0524 ** (−2.27)
Obs.	65	59	54
Adj. *R*-square	0.02	0.07	0.11

Numbers in parentheses are t-statistics. ** and * indicate significant at 5% and 10% significance levels, respectively.

5. Conclusions

A stylized fact concerning corporate acquisitions is that bidding firms experience much smaller returns than the target firms around the acquisition announcement date. This study examined the short-term wealth effect of the merger announcement on the acquiring REIT. Both domestic and cross-border mergers were considered. We tried to reconcile our findings of the wealth effect from a merger announcement on the acquiring REITs with the existing theories and hypotheses on mergers and acquisitions in the corporate finance literature.

When the sample period was divided into pre-crisis, crisis, and after-crisis periods, we found that the acquiring trusts achieved positive and significant abnormal returns around the acquisition announcement date for domestic mergers during the crisis period only. This finding supports the argument that the acquiring REITs took advantage of attractive asset prices during the crisis period [26].

The cross-sectional analysis shows that, before the crisis period, privately held targets and cash-financed deals were positively associated with abnormal returns for the acquiring trusts. Chang [8] argued that when public -private mergers are stock-financed, the acquiring firms achieve positive returns due to the effects of the monitoring hypothesis and the signaling hypothesis. However, our finding cannot be explained by these hypotheses, because acquiring REITs achieved larger abnormal returns when the acquisition was cash-financed rather than stock-financed. During the crisis period, the size of the merger transaction relative to the capitalization of the acquiring trust became positively associated with the abnormal returns to the acquiring trusts. This finding reinforces the argument of the undervalued assets of the target. For example, Reddy et al. [26] found that emerging countries increased their foreign acquisitions in developed countries because of the more attractive asset prices. Following the crisis, the acquiring trusts achieved larger abnormal returns from domestic mergers around the announcement date than that associated with cross-border mergers. Furthermore, if the target trust was privately-held, the acquiring trust achieved smaller abnormal returns around the merger announcement date. Finally, when the acquiring trust had properties in more states, the trust achieved more abnormal returns following the crisis period.

Overall, this study provides evidence which sheds light on the changes in investors' risk preferences after the subprime mortgage crisis. Before the crisis, the acquirer achieved a larger wealth effect from a cross-border merger announcement than that from a domestic merger. This indicates that the benefits resulting from international diversification dominated the losses resulting from cultural differences, investor protection, corporate governance, and valuation differences. During the crisis period, the acquiring REIT achieved larger abnormal returns from the advantage of the undervalued assets of the target REIT. After the crisis, investors became more risk-averse such that the losses resulting from cultural differences, investor protection, corporate governance, and valuation differences dominated the benefits resulting from international diversification. The acquiring REIT also achieved larger abnormal returns around the acquisition announcement date when the acquiring trust had properties in more states.

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Article

Confucius and Herding Behaviour in the Stock Markets in China and Taiwan

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Abstract: It has been argued in the literature that financial markets with a Confucian background tend to exhibit herding behaviour, or correlated behavioural patterns in individuals. This paper applies the return dispersion model to investigate financial herding behaviour by examining index returns from the stock markets in China and Taiwan. The sample period is from 1 January 1999 to 31 December 2014, and the data were obtained from Thomson Reuters Datastream. Although the sample period finishes in 2014, the data are more than sufficient to test the three hypotheses relating to the stock markets in China and Taiwan, both of which have Confucian cultures. The empirical results demonstrate significant herding behaviour under both general and specified markets conditions, including bull and bear markets, and high-low trading volume states. This paper contributes to the herding literature by examining three different hypotheses regarding the stock markets in China and Taiwan, and showing that there is empirical support for these hypotheses.

Keywords: herding behaviour; Confucian background; emerging market; frontier market; China market; Taiwan market

JEL Classification: B26; C58; D53; P34

1. Introduction

Herding is typically associated with a correlated behavioural pattern across individuals, and hence represents human behaviour that mimics the actions of other individuals. Numerous studies have emphasised that herding behaviour can be rational as well as irrational. Moreover, there are alternative types of such behaviour, such as information-based, reputation-based, compensation-based, and spurious herding forms [1,2].

Sequential decision theory states that each trader observes decisions made by others in making their own decisions. This is rational as the decisions of others can include useful information [3–10].

This paper is concerned with the stock markets of China and Taiwan. Stock markets in China provide an interesting insight for the analysis of herding behaviour. Since the establishment of the Shanghai Stock Exchange and the Shenzhen Stock Exchange in December 1990, two classes of shares have been issued, namely: (i) A-shares, which can be purchased and traded only by Chinese domestic investors, and are denominated in the local currency, the Renminbi; and (ii) B-shares, which were sold only to foreign investors before February 2001, after which they have been sold to both foreign and domestic investors. A-shares and B-shares are traded simultaneously on the Shanghai and Shenzhen exchanges.

The characteristics of investors of A-shares and B-shares are very different. A-shares are used by domestic individuals, who typically lack significant knowledge and experience in financial investments. The market for B-shares is dominated by foreign institutional investors, who tend to be more knowledgeable and sophisticated than A-share investors. The different characteristics of A-share and B-share investors may result in differences in the level of herding in each market, especially as the A-share market is relatively immature compared to its B-share counterparts [1,11,12].

Having been established in 1961, which is much earlier than the creation of the stock markets in China, the Taiwan stock market is dominated by domestic individual investors, rather than institutional and foreign investors. Most individual investors tend to have less professional knowledge and cannot access information accurately and easily. However, there has been an increasing interest in the Taiwan stock market by foreign investors in recent years, following the lifting of trading restrictions on qualified foreign institutional investors in 2000 [13,14].

In a market that is dominated by domestic individual investors with limited access to information, it might be argued that the resulting information asymmetry would lead such individual investors to follow the actions of other investors, with the latter including more well-informed domestic and foreign institutional investors. Despite being what might be described as an emerging market, the Taiwan stock market is nevertheless highly developed (for further details, see Ref. [15]).

Moreover, a common characteristic of the stock markets in China and Taiwan is that they arise from Chinese culture, where Confucian management philosophy has been dominant. In this context, Ref. [16,17] argue that Confucian markets tend to exhibit herding behaviour.

This study has two main contributions to herding literature. First, in addition to Confucian culture, these markets have specific common and contradictory characteristics; specifically, both are Chinese societies, though one has a free market economy under democratic governance, while the other has a market economy supervised under a communist regime. Furthermore, Taiwan is one of the four Tiger economies, whereas China has become the second largest economy in the world. Therefore, we feel that it is worth discussing and comparing these two markets. Second, the paper uses daily trading data covering a period of 16 years.

Although stock markets can and do differ across those that have a Confucian culture and those that do not, the primary purpose of this paper is to compare the stock markets in China and Taiwan, both of which have Confucian cultures. The issue of a control group would be important if the paper were to compare stock markets in countries that have a Confucian culture and those that do not.

For these reasons, this paper examines whether herding exists for China and Taiwan under both general and specific markets conditions, including bull and bear markets, and high-low trading volumes states.

The remainder of the paper is presented as follows. A literature review is given in Section 2. Methodological issues and the data to be used in the empirical analysis are discussed in Section 3, including the cross-sectional standard deviation model, the cross-sectional absolute deviation model, herding in up and down markets, and herding in high and low trading volumes. Three hypotheses are presented in Section 4, namely, whether herding exists in China and Taiwan, the existence of asymmetric herding in bull and bear markets, and also in high and low trading volumes. The empirical analysis is conducted in Section 5, where the outcomes of testing the three hypotheses are analysed. Some concluding remarks are given in Section 6.

2. Literature Review

Parts of the review follow the presentation in Ref. [5,18] examine herding in several international markets, specifically the USA, Hong Kong, Japan, South Korea, and Taiwan, by using daily stock price data from January 1963 to December 1997. The authors use the cross-sectional absolute deviation method, as an extension of Ref. [19]. They find no evidence of herding from the US and Hong Kong markets, and only a small amount from Japan. However, they find significant herding from the markets in South Korea and Taiwan.

The authors also find that macroeconomic information affects the formation of herding behaviour more significantly than firm-specific information. Furthermore, they suggest that stock return dispersion, as a function of market returns, is greater in up markets than in down markets. They also test the model suggested by Ref. [19] and find herding only for the Taiwan market.

Using the model of Ref. [5,12] find evidence of herding behaviour in Chinese A-shares. Owing to issues relating to the acquisition of accurate estimates of beta, as suggested in Ref. [5], the authors use the standard deviation in estimating the return dispersion, as in Ref. [12,19] also test the asymmetric impact of herding behaviour by varying returns, trading volumes, and volatility. They find herding behaviour in A-shares in the Shanghai market under rising market circumstances, with high volumes of trading of stocks and volatility. However, they find no evidence of herding in B-shares.

The main participants of A-share markets, which are considered as frontier markets, are local investors, who tend to lack sufficient talent and experience in finance. Investors in B-share markets, which are considered as emerging markets, are primarily foreigners with greater skills and knowledge of finance than investors in A-shares. For these reasons, Tan et al. [12] argue that the differences between A-shares and B-shares may affect the variance in herding. The authors also test herding and the cross-market information effect, but find no evidence of herding. Accordingly, the dissimilarity can be explained due to differences in the samples.

Lin and Swanson [20] also examine herding behaviour in the Taiwan stock market for 1996–2003, using one of the methods discussed in this paper. However, the authors focus only on foreign investors and the most liquid stocks, without classifying them into sectoral groups. They find no evidence to support the proposition that foreign investors display herding behaviour in this market. Lin et al. [21] examine daily trading data by foreign and domestic institutional investors for the fifty stocks that are most actively traded by institutional investors in Taiwan. The authors find the herding tendencies of stocks to be more prominent for small capitalized stocks with high share turnovers and high return volatility, thereby suggesting that market conditions and firm characteristics are significant factors driving herding behaviour.

Using buying and selling volume data, Chen, Wang, and Lin [13] find that qualified foreign institutional investors demonstrate herding behaviour in the Taiwan stock market. The authors show that industry effects, in addition to firm characteristics such as high previous returns and large market capitalization, explain the herding behaviour of foreign institutional investors.

Demirer, Kutan, and Chen [22] measure herding behaviour with daily data regarding stock returns for 689 stocks on the Taiwan Stock Exchange from January 1995 to December 2006. The authors use the models of Ref. [4,19] in addition to state space models. They find no evidence of herding in the model of Ref. [19], but find significant evidence in the non-linear model of Ref. [4] and the state space-based models in Ref. [23]. The authors also find that herding behaviour is stronger during periods of market losses than market gains.

Consequently, this paper suggests that investors need more diversified opportunities in periods of market losses. The authors emphasise the following in their analysis: (i) interesting and novel empirical results for an emerging yet relatively sophisticated Taiwan stock market at the sectoral level with firm-level data; (ii) an application of different models; and (iii) an analysis of the practical implications of different herding measures for investors who face both systematic and unexpected risks.

Yao, Ma, and He [24] measure the existence of herding behaviour in the China A-share and B-share markets. They use daily and weekly firm-level and market-level data of equity prices for all firms and indexes that are listed on the Shanghai Stock Exchange and the Shenzhen Stock Exchange from January 1999 to December 2008. Monthly data are also collected for all firms included in the data set. For the empirical analysis in testing herding behaviour, the authors use a modified version of the models of Ref. [4,19].

The empirical results show that herding behaviour is heterogeneous, so that herding is stronger in Chinese B-shares. In addition, the authors find that cross-market herding behaviour is stronger at the industry level, for the largest and smallest stocks, and for growth stocks relative to value stocks. The empirical results show that herding behaviour is greater when share prices are declining. Finally, the authors find that herding behaviour is affected by the regulatory reforms in China that are intended to increase investment efficiency.

In exploring the determinants of investment decision-making in international stock markets, Chang and Lin [16] analyse herding in daily market returns data and industrial index data for 50 stock markets for the cross-sectional absolute deviation of returns. The analysis uses an extended version of the model in Ref. [4]. In order to investigate the influence of culture on herding behaviour, the authors examine the Hofstede national culture indexes for the empirical analysis. In order to test behavioural pitfalls on the herding tendency, the authors use daily data of price-to-book ratios as proxies for excessive optimism, and daily trading volumes data are used as proxies for overconfidence and disposition.

The data set ranges from January 1965 to July 2011. The authors argue that their research examines the effects of culture and behavioural pitfalls in investments, and show that herding is exhibited in Confucian, as well as in less sophisticated stock markets. Moreover, the authors find that some cultural indexes have a high degree of correlation with herding behaviour.

3. Methodology and Data

3.1. Data

Ref. [12,19] find that the average cross-sectional absolute deviation (CSAD) calculated with the use of daily data is smaller than with the use of weekly or monthly data. This difference reflects the fact that, with weekly or monthly data, individual returns have a greater opportunity to stray further from the mean. Consequently, herding is less likely to be detected with weekly or monthly data. For this reason, this paper uses daily stock returns data for all firms on the Shanghai Stock Exchange (SSE), the Shenzhen Stock Exchange (SZSE), and the Taiwan Stock Exchange.

There are 425 Shanghai A-share firms (SHA) and 50 Shanghai B-share firms (SHB) at the SSE, 415 Shenzhen A-share firms (SZA) and 45 Shenzhen B-share firms (SZB) at the SZSE, and 455 firms comprising the Taiwan Capitalization Weighted Stock Index (TAIEX). In addition, we use daily index price data in each corresponding market. The data period spans from 1 January 1999 to 1 January 2015. A-share markets are considered as frontier markets, while both B-share markets and TAIEX are classified as emerging markets. The data are obtained from the Thomson Reuters Datastream database. The simple return method is used to calculate market returns and stock returns.

3.2. Methodology

The return dispersion method is a widely-used approach in most herding studies because it is a reliable method to measure herding behaviour. In the following subsections, we discuss several return dispersion models that are used in this paper.

3.2.1. Cross-Sectional Standard Deviation Model

Ref. [4,19] use individual stock returns and market returns to detect herding behaviour. Christie and Huang [19] propose the following cross-sectional standard deviation (CSSD) model to detect herding behaviour:

$$CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t \quad (1)$$

where

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t} - R_{m,t})^2}{(N-1)}}$$

at time t is the cross-sectional standard deviation; D_t^L is a dummy variable of unity when market returns at t lie in the extreme lower tail returns, and zero otherwise; D_t^U is a dummy variable of one when market returns at t lie in the extreme upper tail returns, and zero otherwise; α is a constant, both β^L and β^U are coefficients of D_t^L and D_t^U, respectively; ε_t is a random error term; N is the number of firms; and $R_{i,t}$ and $R_{m,t}$ are individual stock returns of stock i and market returns, respectively.

The model argues that if herding occurs when market returns lie in the extreme lower tail returns, then the estimate of β^L will be significantly negative. On the other hand, if herding occurs when market returns lie in the extreme upper tail returns, then the estimate of β^U will be significantly negative.

3.2.2. Cross-Sectional Absolute Deviation Model

One of the challenges associated with the CSSD model is that it must define extreme returns. Arguing that the definition in the CSSD model is arbitrary, Christie and Huang [19] suggest using 1% and 5% as the cut-off points of the upper and lower tails of returns. In practice, investors may have different opinions regarding extreme returns, and it is possible that the returns will change dynamically.

In addition, herding behaviour may occur for the return distribution, but become more pronounced with market stress. Consequently, Christie and Huang [19] suggest that herding might be captured only for extreme returns. Ref. [4,25] suggest that Christie and Huang's [19] approach is too stringent to discover any empirical evidence of herding.

3.2.3. Herding Behaviour

Ref. [4,12,25] suggest using the following cross-sectional absolute deviation (CSAD) model:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \varepsilon_t \tag{2}$$

to facilitate the detection of herding for all returns where, at time t, the cross-sectional absolute deviation given by:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|R_{i,t} - R_{m,t}|$$

is a measure of the average absolute return dispersion from $R_{m,t}$ to measure the return dispersion, and $|R_{m,t}|$ and $R_{i,t}$ are the absolute value of market returns and individual stock returns of stock i, respectively.

If one analyses more than one financial market, it is possible to use the following model:

$$CSAD_{i,t} = \alpha + \gamma_1 |R_{i,m,t}| + \gamma_2 (R_{i,m,t})^2 + \varepsilon_{i,t} \tag{3}$$

where, for market i at time t, $CSAD_{i,t}$ is the return dispersion calculated according to Equation (2), α is a constant, $|R_{i,m,t}|$ is the absolute value of market returns, $(R_{i,m,t})^2$ is the squared value of market returns, and $\varepsilon_{i,t}$ is a random error term.

3.2.4. Herding Behaviour in Up and Down Markets

As the direction of market returns may affect investor behaviour, it is sensible to examine whether there is any asymmetry in herding behaviour, conditional on the market rising or falling. The herding regression model is estimated separately for positive and negative market returns. Specifically, the two-equation system can be written as:

$$CSAD_{i,t}^{UP} = \alpha + \gamma_1^{UP}\left|R_{i,m,t}^{UP}\right| + \gamma_2^{UP}\left(R_{i,m,t}^{UP}\right)^2 + \varepsilon_{i,t} \text{ If } R_{i,m,t} > 0 \tag{4}$$

$$CSAD_{i,t}^{DOWN} = \alpha + \gamma_1^{DOWN}\left|R_{i,m,t}^{DOWN}\right| + \gamma_2^{DOWN}\left(R_{i,m,t}^{DOWN}\right)^2 + \varepsilon_{i,t} \text{ If } R_{i,m,t} < 0 \tag{5}$$

where, for market i at t, $CSAD_{i,t}^{UP}$ is the return dispersion when markets rise, α is a constant, $\left|R_{i,m,t}^{UP}\right|$ is the absolute value of market returns when the market rises, $\left(R_{i,m,t}^{UP}\right)^2$ is the squared value of market returns when the market rises, and $\varepsilon_{i,t}$ is a random error term. Variables with the superscript *DOWN* in Equation (5) refer to market falls. The variable $CSAD_{i,t}$ for each market in Equations (4) and (5) is defined in Equation (2). A negative and significant estimated coefficient γ_2^{UP} or γ_2^{DOWN} would indicate the presence of herding.

3.2.5. Herding Behaviour in High and Low Trading Volumes

The level of herding behaviour may be associated with the trading volume. For this reason, it is possible to examine any asymmetric effects during periods of high and low trading volume. The trading volume is given the superscript *HIGH* if the trading volume on day *t* is greater than the moving average for the previous 30 days. The trading volume is given the superscript *LOW* if it is less than the moving average for the previous 30 days. We also checked moving averages for periods of 7 and 90 days.

The empirical results of this paper are different from those in Tan et al. (2008), who use longer time periods of 60, 90, and 120 days. We used shorter time periods because many studies (for example, Chang et al. [4] suggest that the sentiment of investors typically occurs in a relatively short period of time. Therefore, we tested the following empirical models:

$$CSAD_{i,t}^{TV-HIGH} = \alpha + \gamma_1^{TV-HIGH}\left|R_{i,m,t}^{TV-HIGH}\right| + \gamma_2^{TV-HIGH}\left(R_{i,m,t}^{TV-HIGH}\right)^2 + \varepsilon_{i,t} \tag{6}$$

$$CSAD_{i,t}^{TV-LOW} = \alpha + \gamma_1^{TV-LOW}\left|R_{i,m,t}^{TV-LOW}\right| + \gamma_2^{TV-LOW}\left(R_{i,m,t}^{TV-LOW}\right)^2 + \varepsilon_{i,t} \tag{7}$$

where, in market i at t, $CSAD_{i,t}^{TV-HIGH}$ is the return dispersion when the trading volume is high, α is an intercept term, $\left|R_{i,m,t}^{TV-HIGH}\right|$ is the absolute value of market returns when the trading volume is high, $\left(R_{i,m,t}^{TV-HIGH}\right)^2$ is the squared value of market returns when the trading volume is high, and $\varepsilon_{i,t}$ is a random error term.

Similarly, variables with the superscript *TV-LOW* refer to low trading volumes, where the superscript *TV* refers to trading volume. The variable $CSAD_{i,t}$ in Equations (6) and (7) is calculated using Equation (2). A negative and statistically significant estimated coefficient $\gamma_2^{TV-HIGH}$ or γ_2^{TV-LOW} would indicate herding.

4. Three Hypotheses of Herding Behaviour

There are three hypotheses regarding herding behaviour that will be tested in this paper. They are discussed separately in the following subsections.

4.1. First Hypothesis

Theoreticians and practitioners alike believe that there is herding behaviour in stock markets. It is hypothesised that this phenomenon also holds for the China and Taiwan stock markets. Therefore, we present the following hypothesis to test whether any herding exists in stocks in China and Taiwan:

Hypothesis 1. *Herding behaviour exists in the stock markets in China and Taiwan.*

We note that there are different factors that may induce herding behaviour, including a high degree of government involvement in equity markets and heavy interest rate intervention by the central bank.

In this paper, we use Equation (8) to test Hypothesis 1. A negative and statistically significant estimated coefficient γ_2 would indicate herding. We note that γ_1 in Equation (3) [and also in Equation (2) cannot be used to test Hypothesis 1. However, γ_1 is positive, implying that there is a linear relationship between the cross-sectional absolute deviation of returns, $CSAD_t$, and $|R_{i,m,t}|$. In addition, from Equation (3), we have a quadratic function for $CSAD_t$ and $|R_{i,m,t}|$:

$$CSAD_{i,t} = \alpha + \gamma_1 |R_{i,m,t}| + \gamma_2 (R_{i,m,t})^2 \tag{8}$$

where $CSAD_t$ reaches its maximum value when:

$$|R_{i,m,t}|^* = -\left(\frac{\gamma_1}{2\gamma_2}\right)$$

If $|R_{i,m,t}|$ increases when the realised average daily returns in absolute terms are less than $|R_{i,m,t}|^*$, $CSAD_t$ is still associated with an increasing trend. However, as $|R_{i,m,t}|$ exceeds $|R_{i,m,t}|^*$, then $CSAD$ starts to increase at a decreasing rate, which is captured by a negative and significant estimated coefficient γ_2. Therefore, the non-linear relationship between the market returns and the return dispersion would indicate herding behaviour. For this reason, a non-linear market return $(R_{i,m,t})^2$ is included in the equation.

However, if market participants tend to follow aggregate market behaviour and ignore their own priors during periods of large average price movements, then the linear and increasing relation between dispersion and market returns will no longer hold. Instead, the proposed relationship could increase non-linearly, or even decrease non-linearly. The empirical model builds on this intuition.

4.2. Second Hypothesis

It is well-known that stock markets perform differently in bull runs and bear markets [26,27]. Some studies, for example, Ref. [28], have found that herding behaviour can be different in bull runs and bear markets. It is common (see Ref. [29,30]) for the negative fear of potential loss when the market crashes to exceed the positive effects of potential gains under market booms. McQueen, Pinegar, and Thorley [31] claim that this is because while all stocks tend to respond quickly to negative macroeconomic news, small stocks tend to be slow in reacting to positive news.

As positive news often entails an increase in stock prices, a slow reaction implies a delay in reacting to good news. Therefore, herding is more pronounced during market downturns than upturns [24,28,32].

It is hypothesised that these phenomena also hold for the stock markets in China and Taiwan. Consequently, we propose the following hypothesis to test whether investors tend to display herding behaviour more in downturns than upturns:

Hypothesis 2. *Asymmetric herding behaviour exists in the stock markets in both China and Taiwan during bull and bear markets.*

Hypothesis 2 states that herding exists in bull and bear markets in the stock markets in China and Taiwan if the estimated coefficients γ_2^{UP} and γ_2^{DOWN} in Equations (4) and (5), respectively, are significantly different from zero. Chang et al. (2000) have shown that when γ_1^{UP} and γ_1^{DOWN} reach a certain value, both $CSAD_{i,t}^{UP}$ and $CSAD_{i,t}^{DOWN}$ start to decrease, or at least increase less proportionately with the market returns because there is a non-linear relationship between return dispersion and market returns. Therefore, γ_1^{UP} and γ_1^{DOWN} cannot be used to test Hypothesis 2, according to which herding exists in both bull and bear markets.

4.3. Third Hypothesis

It is also well-known (see Ref. [33]) that stock returns depend on the magnitude of the trading volume. In addition, the relationship between stock returns and trading volume is different for different levels of herding behaviour under alternative market conditions [24,34].

It is hypothesised that these phenomena also hold for the stock markets in China and Taiwan. Therefore, we propose the following hypothesis to test whether the level of herding behaviour is associated with trading volume:

Hypothesis 3. *Asymmetric herding behaviour exists in the stock markets in both China and Taiwan in high and low trading volumes.*

We confirm Hypothesis 3 that herding exists in the high and low volatility states of the stock markets in China and Taiwan if the estimated coefficients $\gamma_2^{TV-HIGH}$ and γ_2^{TV-LOW} in Equations (6) and (7), respectively, are significantly different from zero. Chang et al. (2000) have shown that when $\gamma_1^{TV-HIGH}$ or γ_1^{TV-LOW} reaches a certain value, $CSAD_{i,t}^{TV-HIGH}$ or $CSAD_{i,t}^{TV-LOW}$ will start to decrease, or at least increase less proportionately with the market returns because there is a non-linear relationship between return dispersion and market returns. Therefore, $\gamma_1^{TV-HIGH}$ or γ_1^{TV-LOW} cannot be used to test Hypothesis 3, according to which herding exists in high and low volatility states in the stock markets in China and Taiwan.

5. Empirical Analysis

5.1. Descriptive Statistics

This paper applies the CSAD return dispersion model, as given in Equations (2)–(7), and tests Hypotheses 1–3 to investigate whether there is any herding behaviour by examining the index returns from the stock markets in China and Taiwan. In order to do so, we first estimated the univariate descriptive statistics for the return dispersion and market returns of the markets in China and Taiwan. By definition, CSAD takes on a minimum value of zero when all individual stock returns move in perfect unison with the market, and increases when the returns of individual stocks deviate from the market returns.

Table 1 shows the descriptive statistics of market returns and CSAD return dispersions for the stock markets in both China and Taiwan. The average daily returns range from a low of 0.0129% for the TAIEX market to a high of 0.0899% for the SZB market. Daily returns of B-share markets consistently have higher mean values than those of A-shares markets, along with higher standard deviations. This evidence is consistent with the findings in Chang et al. (2000) and Tan et al. (2008) in that, in more well-developed markets, the greater the mean values of market returns and the higher the volatility.

The lowest daily returns (−9.780) were observed on 6 August 2001 in the SHB market, while the second lowest minimum daily returns (−9.493) were observed on 6 July 1999 in the SZB market. Maximum daily returns also occurred around the same time. The lowest and highest daily returns were observed in the B-share markets as the B-shares were made accessible to foreign investors from February 2001.

The descriptive statistics show that the mean values of CSAD for A-shares are consistently higher than those of B-shares, and are also accompanied by higher standard deviations. Chiang and Zheng [35] argue that higher standard deviations in similar markets suggest that the markets had unusual cross-sectional variations due to unexpected news or shocks. The TAIEX market also has a relatively high mean returns dispersion, which is accompanied by the lowest standard deviation.

This observation is consistent with the herding behaviour according to which investors in the TAIEX market are more likely to react efficiently to news and diverse shocks. One explanation is that sophisticated investors in emerging markets have more information and analytical tools that allow them to assess and reallocate their investments, thereby leading to a higher dispersion of stock returns and lower standard deviations.

Table 1. Descriptive statistics of cross-sectional absolute deviation (CSAD) and market returns of the stock markets in China and Taiwan.

	SHA		SHB		SZA		SZB		TAIEX	
	CSAD	R_m	CSAD	R_m	CSAD	R_m	CSAD	R_m	CSAD	R_m
Mean	1.504 ***	0.028	1.107 ***	0.076 **	1.453 ***	0.038	1.272 ***	0.089 ***	1.549 ***	0.012
Std. dev.	0.767	1.511	0.686	2.055	0.684	1.656	0.693	1.957	0.656	1.398
Minimum	0	−8.845	0	−9.780	0	−8.539	0	−9.493	0	−9.460
Maximum	7.220	9.856	5.129	9.914	6.678	9.680	5.287	9.857	6.014	6.740
Skewness	0.835 ***	0.066 *	1.132 ***	0.280 ***	0.589 ***	−0.293 ***	0.773 ***	0.385 ***	0.315 ***	−0.149 ***
Kurtosis	6.225 ***	8.048 ***	5.741 ***	8.446 ***	6.833 ***	6.554 ***	5.044 ***	8.391 ***	5.024 ***	6.308 ***
N obs.	3982		4174		3877		4174		3779	
N firms	425		50		415		45		455	

Note: CSAD is defined as cross-sectional absolute deviation. R_m is the market return. SHA, SHB, SZA, SZB, and TAIEX are stated in Section 4.1. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

In addition to the above results, Ref. [25,31] argue that investors may fear potential losses in downturns more than they enjoy potential gains in upturns. This proposition leads investors to display herding behaviour. The consequence is a reduction in the returns dispersion. The empirical findings in this paper are consistent with such an argument.

The stationarity of the measures of the returns dispersion is evaluated through the implementation of the Augmented Dickey-Fuller (ADF) test. As all the series are found to be stationary, we do not report details of the ADF test results. After reviewing the relevant literature, we have developed the three hypotheses presented in Section 4 to test whether the stock markets in China and Taiwan exhibit herding under different conditions. We discuss each of the hypotheses in the following subsections.

5.2. Testing Herding Behaviour (H1)

In order to test the first proposed hypothesis as to whether there is any herding behaviour in the stock markets in both China and Taiwan, we examined whether the estimated coefficients in Equation (3) are significantly less than zero, as discussed in Section 4.1. The empirical findings are reported in Table 2. According to the definition of the empirical model in Equation (3), a negative and statistically significant estimated coefficient γ_2 would indicate the presence of herding.

Table 2. Results of herding behaviour in the sample stock markets.

Market Name (N)	α	$\gamma 1$	$\gamma 2$	Adj. R^2
SHA (3982)	1.053 (59.32) ***	0.564 (27.33) ***	−0.053 (−15.09) ***	0.249
SHB (4174)	0.668 (48.15) ***	0.479 (32.19) ***	−0.043 (−22.42) ***	0.290
SZA (3877)	1.000 (56.62) ***	0.473 (23.26) ***	−0.035 (−8.55) ***	0.299
SZB (4174)	0.839 (55.36) ***	0.479 (31.15) ***	−0.044 (−21.24) ***	0.273
TAIEX (3779)	1.126 (47.78) ***	0.588 (12.81) ***	−0.072 (−5.47) ***	0.267

Notes: Numbers in parentheses are *t*-statistics from Ref. [36] consistent standard errors. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. This table reports the results of the estimation of the empirical model in Equation (3): $CSAD_{i,t} = \alpha + \gamma_1 |R_{i,m,t}| + \gamma_2 (R_{i,m,t})^2 + \varepsilon_{i,t}$.

Table 2 shows that the estimates of γ_2 are significantly negative in all markets at the 1% level, thereby supporting the first hypothesis and suggesting that there is strong herding behaviour in the Taiwan stock index, TAIEX, and all the Chinese stock indexes, including SHA, SHB, SZA, and SZB. The empirical findings do not reject Hypothesis 1, thereby suggesting that there is significant herding behaviour in the SHB, SZB, and TAIEX stock markets, which are emerging markets. These results are consistent with the empirical findings in Ref. [4,12,16].

The coefficients on the linear component of $|R_{i,m,t}|$ are positive and significant, thereby indicating that there is both a significant and positive linear relationship between $CSAD_{i,t}$ and $|R_{i,m,t}|$. Table 2 shows that the combined effects of the herding effect and the linear relationship between $CSAD_{i,t}$ and $|R_{i,m,t}|$ explain from 24.9% (SHA) to 29.9% (SZA) of the total variation in $CSAD_{i,t}$. In addition, substituting the estimated coefficients for the SHA market ($\gamma_1 = 0.564$ and $\gamma_2 = -0.053$) into the quadratic relationship in Equation (8) indicates that $CSAD_t$ reaches a maximum when the following holds:

$$|R_{i,m,t}| = |R_{i,m,t}|^* = 5.321\%$$

This outcome suggests that, during large price movements in market returns that exceed the threshold level $|R_{i,m,t}|^*$, the $CSAD_t$ increases at a decreasing rate, as in Figure 1.

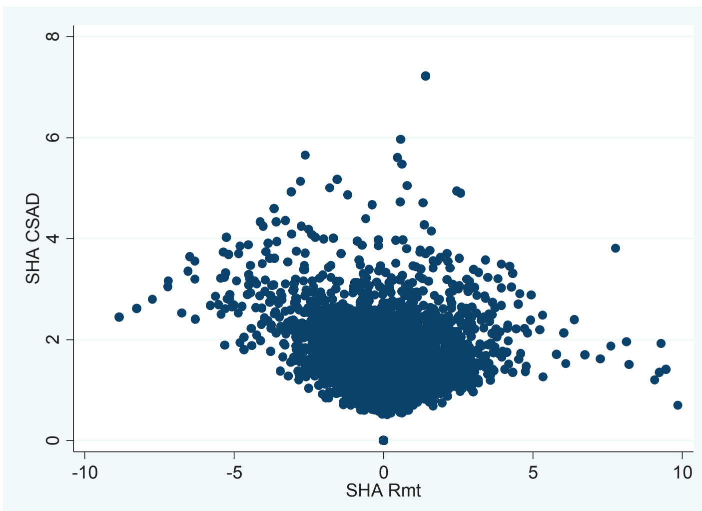

Figure 1. Relationship between the daily return dispersion ($CSAD_{i,t}$) and equally-weighted market return ($R_{i,m,t}$) for the SHA market.

In addition to the negative and statistically significant estimated coefficient, γ_2, the sizes of the coefficient capture the magnitudes of the herding behaviour in each market [34]. As the largest value of the estimated coefficient, γ_2, is found in the TAIEX market (as measured at -0.072), while the smallest value lies in the SZA market (as measured at -0.035), the estimated coefficients show that herding behaviour is greater in the TAIEX market than in the emerging markets in China.

5.3. Testing Herding Behaviour in Up and Down Markets (H2)

The second hypothesis tests whether herding is asymmetric in the stock markets in China and Taiwan when they rise and fall. Table 3 reports the outcomes in testing the second hypothesis. According to the models in Equations (4) and (5), the negative and statistically significant estimated coefficients, γ_2^{UP} and γ_2^{DOWN}, respectively, indicate that there is herding behaviour due to the up and down markets. If the magnitudes of γ_2^{UP} and γ_2^{DOWN} are different, then the additional herding behaviours due to the up and down markets are different, thereby showing that herding behaviour is asymmetric in both up and down markets.

Table 3. Results of herding behaviour in the stock markets in China and Taiwan in up and down markets.

Market Name (N)	UP Market $R_{i,m,t} > 0$				Market Name (N)	DOWN Market $R_{i,m,t} < 0$			
	α	$\gamma 1^{UP}$	$\gamma 2^{UP}$	Adj. R^2		A	$\gamma 1^{DOWN}$	$\gamma 2^{DOWN}$	Adj. R^2
SHA (2224)	0.916 (39.79) ***	0.605 (22.96) ***	−0.066 (−13.97) ***	0.236	SHA (1758)	1.309 (53.61) ***	0.391 (11.65) ***	−0.015 (−2.39) **	0.272
SHB (2314)	0.560 (31.99) ***	0.546 (28.29) ***	−0.051 (−21.42) ***	0.337	SHB (1860)	0.840 (40.19) ***	0.356 (15.46) ***	−0.027 (−8.32) ***	0.227
SZA (2237)	0.862 (38.75) ***	0.551 (22.31) ***	−0.059 (−11.78) ***	0.284	SZA (1640)	1.288 (58.35) ***	0.291 (11.73) ***	−0.000 (−0.01)	0.338
SZB (2372)	0.700 (36.27) ***	0.581 (30.21) ***	−0.056 (−24.63) ***	0.329	SZB (1802)	1.082 (50.06) ***	0.282 (11.34) ***	−0.017 (−4.39) ***	0.197
TAIEX (2058)	0.960 (39.23) ***	0.783 (23.80) ***	−0.111 (−12.78) ***	0.329	TAIEX (1721)	1.332 (50.91) ***	0.381 (8.02) ***	−0.034 (−2.62) ***	0.199

Notes: Numbers in parentheses are *t*-statistics based on Ref. [36] consistent standard errors. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. This table reports the results of the estimation of the empirical model in Equations (4) and (5): $CSAD_{i,t}^{UP} = \alpha + \gamma_1^{UP}\left|R_{i,m,t}^{UP}\right| + \gamma_2^{UP}\left(R_{i,m,t}^{UP}\right)^2 + \varepsilon_{i,t}$ if $R_{i,m,t} > 0$ $CSAD_{i,t}^{DOWN} = \alpha + \gamma_1^{DOWN}\left|R_{i,m,t}^{DOWN}\right| + \gamma_2^{DOWN}\left(R_{i,m,t}^{DOWN}\right)^2 + \varepsilon_{i,t}$ if $R_{i,m,t} < 0$.

Table 3 shows that the estimated coefficient, γ_2^{UP}, is negative and statistically significant in all markets at the 1% level, thereby implying that there is herding behaviour due to the up markets in all cases that have been considered. However, the coefficient, γ_2^{DOWN}, is negative and statistically significant at the 1% level only for SHB, SZB, and TAIEX, significant at the 5% level for SHA, and not significant for SZA. These results suggest that there is herding behaviour due to the down markets for SHB, SZB, TAIEX, and SHA, but not for SZA. It follows that Hypothesis 2 is rejected only for the SZA market.

For SZA, as the estimated coefficient γ_2^{UP} is significant, while the estimated coefficient γ_2^{DOWN} is not significant, it follows that herding behaviour is asymmetric in the up and down markets, respectively. In addition, for SHB, SZB, TAIEX, and SHA, as both the estimated coefficients, γ_2^{UP} and γ_2^{DOWN}, are significant, but of different magnitudes, the herding behaviour is asymmetric in the up and down markets. Therefore, Hypothesis 2 is supported empirically for the SHB, SZB, TAIEX, and SHA markets.

The outcomes of the tests of Hypothesis 2 are consistent with the empirical results as reported in Ref. [12,35]. A possible explanation for these findings is that institutional investors in the China and Taiwan stock markets may engage in positive feedback trading by buying additional shares when prices are rising, and selling them when the prices are falling [37,38]. However, the empirical findings in this paper are different from those in Ref. [4,24,31,34], among others, who find that investors behave more homogeneously when stock markets are declining.

Breaking down the up and down markets, the up market states are bull markets that are characterized by optimism under a strong economy, with confident investors who expect stock prices to continue rising [39,40]. On the other hand, down markets are bear markets that are characterized by falling prices and shrouded in pessimism. Bear markets typically occur before the economy starts to contract [15,41].

5.4. Testing Herding Behaviour during HIGH and LOW Trading Volume States (H3)

The third hypothesis conjectures that asymmetric herding exists in the China and Taiwan stock markets during high and low trading volume states. Table 4 reports the empirical results in testing the third hypothesis. According to the definitions in Equations (6) and (7), negative and statistically significant estimated coefficients, $\gamma_2^{TV-HIGH}$ and γ_2^{TV-LOW}, indicate herding behaviour in the high and low trading volume states, respectively.

The results in Table 4 show that the estimated coefficient, $\gamma_2^{TV-HIGH}$, is negative and statistically significant for all the markets, except for SZA.

On the other hand, the estimated coefficient, γ_2^{TV-LOW}, is negative and significant in all markets at the 1% level, thereby implying that there is a strong indication of herding in all markets during the low trading states. For SZA, as the estimated coefficient, $\gamma_2^{TV-HIGH}$, is negative, but not significant, while the estimated coefficient, γ_2^{TV-LOW}, is significantly negative, it follows that herding behaviour is asymmetric in the up and down markets, respectively.

In short, the empirical findings strongly suggest that there is evidence of herding in sample markets when the trading volume is either high or low. Nonetheless, herding is greater when the trading volume is low than when it is high. A possible explanation is that, during low trading volume states, less trading happens, and thus share returns become naturally more homogenous and correlated, which can lead to ineffective herding behaviour.

Ref. [12,24] find that herding is greater when the trading volume is high. It is worth noting that the empirical results in this paper find that herding behaviour is greater when the trading volume is high. However, it is also found that herding is even greater when the trading volume is low, which is also in line with the findings of Ref. [28].

This paper also examines Hypothesis 3 with moving averages of 7 and 90 days. The empirical results show that the 7-day and 90-day moving averages are consistent with the use of 30-day moving averages. In summary, the empirical results provide very strong evidence in favour of Hypothesis 3.

Table 4. Results of herding behaviour in the China and Taiwan stock markets during HIGH and LOW trading volume states.

Market Name (N)	$TV^{HIGH} > TV^{MA}{}_{t-30}$				Market Name (N)	$TV^{LOW} < TV^{MA}{}_{t-30}$			
	α	$\gamma 1^{TV\text{-}HIGH}$	$\gamma 2^{TV\text{-}HIGH}$	Adj. R^2		α	$\gamma 1^{TV\text{-}LOW}$	$\gamma 2^{TV\text{-}LOW}$	Adj. R^2
SHA (2003)	1.423 (58.53) ***	0.297 (10.03) ***	−0.022 (−3.83) ***	0.111	SHA (1949)	0.790 (34.87) ***	0.800 (25.31) ***	−0.082 (−12.93) ***	0.371
SHB (1783)	0.962 (37.21) ***	0.3224 (14.24) ***	−0.027 (−9.74) ***	0.155	SHB (2361)	0.532 (35.06) ***	0.542 (28.41) ***	−0.052 (−18.29) ***	0.341
SZA (1975)	1.357 (56.70) ***	0.211 (6.85) ***	−0.005 (−0.79)	0.167	SZA (1872)	0.752 (34.08) ***	0.670 (23.93) ***	−0.05 (−8.40) ***	0.421
SZB (1770)	1.150 (45.40) ***	0.319 (14.12) ***	−0.027 (−9.20) ***	0.156	SZB (2374)	0.689 (39.9) ***	0.542 (26.19) ***	−0.054 (−15.88) ***	0.306
TAIEX (1835)	1.382 (55.5) ***	0.416 (10.38) ***	−0.042 (−3.78) ***	0.198	TAIEX (1914)	0.953 (28.32) ***	0.653 (8.38) ***	−0.082 (−14.05) ***	0.307

Notes: Numbers in parentheses are *t*-statistics based on Ref. [36] consistent standard errors. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Thirty-day moving averages of trading volume (TV) are given when TV is high and low. This table reports the results of the estimation of Equations (6) and (7): $CSAD_{i,t}^{TV-HIGH} = \alpha + \gamma_1^{TV-HIGH}\left|R_{i,m,t}^{TV-HIGH}\right| + \gamma_2^{TV-HIGH}\left(R_{i,m,t}^{TV-HIGH}\right)^2 + \varepsilon_{i,t}$, $CSAD_{i,t}^{TV-LOW} = \alpha + \gamma_1^{TV-LOW}\left|R_{i,m,t}^{TV-LOW}\right| + \gamma_2^{TV-LOW}\left(R_{i,m,t}^{TV-LOW}\right)^2 + \varepsilon_{i,t}$.

6. Concluding Remarks

As it has been argued in the literature that markets with a Confucian background are more likely to exhibit herding behaviour, this paper examined the stock markets in China and Taiwan through empirical analysis. There was overwhelming evidence of herding behaviour from the full sample markets. The three hypotheses were tested against empirical evidence, and were all supported by the data.

In respect to the first hypothesis, there was significant herding from all markets, regardless of whether they were emerging or frontier markets.

In addition to testing the second and third hypotheses, it was found that herding is greater in up markets than in down markets, and was also greater during low trading volume states than during high trading volumes. The up markets are positive and profitable for investors, and are key features of bull markets. During a bull market, investors are more optimistic with regards to trading.

However, this does not mean that investors make decisions entirely on they own. When investors are overly optimistic, they exhibit risky behaviour by making risky investment decisions, such as buying too many stocks, based either on their own decisions or by following other traders [40]. Therefore, bull markets might be creating a foundation for possible herding behaviour.

Moreover, previous research has suggested that one of the indicators of down markets is a reduction in trading volume, which follows uncertainty among investors. Investors perceive falls in trading volume with an understandable fear that the market might also fall. Consequently, investors are more likely to convert shares into fast cash [39,42].

Therefore, this sentiment makes the fear among investors contagious, thereby leading to the formation of herding. On the other hand, in bear markets, markets cool down and less trading happens, and thus stock returns become less diverse and more correlated, which may lead to ineffective herding behaviour.

In general, this paper detected overwhelming herding from the entire sample markets. For this reason, all three hypotheses were supported strongly by the data. This paper analysed the stock markets of China and Taiwan empirically based on 15 years of daily observations, which offers another contribution to the literature on herding. Although the sample period finishes in 2014, the data are more than sufficient to test the three hypotheses relating to the stock markets in China and Taiwan, both of which have Confucian cultures.

Although the stock market in Taiwan is relatively developed compared to the markets in China, it still displayed strong herding behaviour. Therefore, further research is necessary to examine herding behaviour beyond the maturity of market settings. Moreover, the authors of this paper intend to include non-Confucian markets as a control group in future research to ascertain if herding behaviour is found in Confucian and non-Confucian countries.

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An Event Study Analysis of Political Events, Disasters, and Accidents for Chinese Tourists to Taiwan

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Abstract: The number of Chinese tourists visiting Taiwan has been closely related to the political relationship across the Taiwan Strait. The occurrence of political events and disasters or accidents have had, and will continue to have, a huge impact on the Taiwan tourism market. To date, there has been relatively little empirical research conducted on this issue. Tourists are characterized as being involved in one of three types of tourism: group tourism (group-type), individual tourism (individual-type), and medical cosmetology (medical-type). We use the fundamental equation in tourism finance to examine the correlation that exists between the rate of change in the number of tourists and the rate of return on tourism. Second, we use the event study method to observe whether the numbers of tourists have changed abnormally before and after the occurrence of major events on both sides of the Strait. Three different types of conditional variance models, namely, the Generalized Autoregressive Conditional Heteroscedasticity, GARCH (1,1), Glosten, Jagannathan and Runkle, GJR (1,1) and Exponential GARCH, EGARCH (1,1), are used to estimate the abnormal rate of change in the number of tourists. The empirical results concerning the major events affecting the changes in the numbers of tourists from China to Taiwan are economically significant, and confirm the types of tourists that are most likely to be affected by such major events.

Keywords: event study; abnormal rate of change; Chinese tourists; OLS; GARCH; GJR; EGARCH; tourism finance

JEL: G14; C22; C52; C58

1. Introduction

According to statistics compiled by Taiwan's Tourism Bureau under its Ministry of Transportation and Communications for the year 2016, international visitors to Taiwan mostly came from five regions, namely, China and Hong Kong (including Macao), Japan, South Korea, Malaysia, and Singapore. However, from 2010 onwards, with the relaxation of the Cross-Strait tourism policy, the number of tourists to Taiwan from China markedly increased, reaching 3.43 million by the end of 2015, accounting for 45.80% of the total number of international visitors to Taiwan. The number of Chinese tourists in 2016, nevertheless, appears to have exhibited a significantly downward trend (see Figure 1).

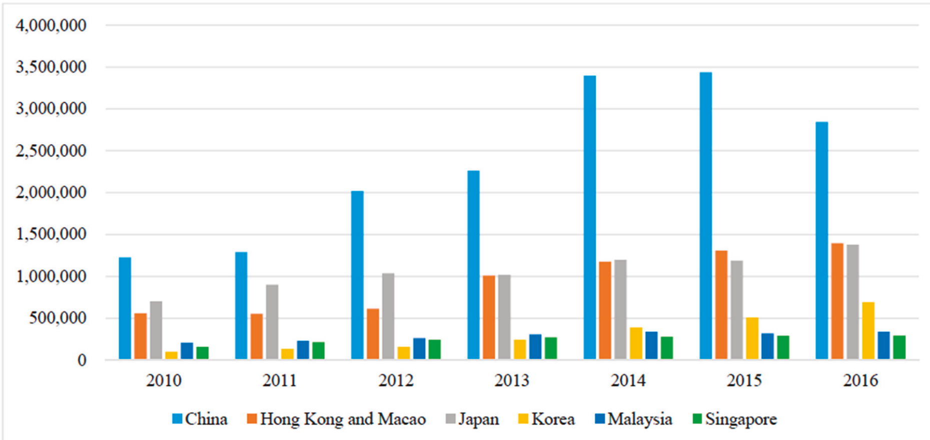


Figure 1. Top five international tourist arrivals to Taiwan, 2010–2016. Sources: Taiwan Tourism Bureau (2017).

The number of Chinese tourists coming to Taiwan has been very closely related to the political relationship across the Taiwan Strait. Beginning in 1949, when the Chinese Communist Party announced the establishment of the People's Republic of China, and the Republic of China relocated to Taiwan, a period of mutual confrontation and division between the two sides ensued, and both sides held fast to the principle of there being only one China. In 1987, after Taiwan announced the lifting of martial law, citizens of Taiwan were allowed to travel to China to visit relatives.

On 1 January 2001, Taiwan piloted its "Three Small Links" policy, whereby mainland Chinese were allowed to apply to visit the offshore islands of Kinmen and Matsu for sightseeing, and passengers on both sides of the Taiwan Strait could travel to and from these islands. On 1 January 2002, mainland Chinese who had gone overseas to study, or who had acquired permanent residence in another foreign country, were allowed to visit Taiwan. On 1 May 2002, mainland Chinese who were allowed to travel on business trips abroad were permitted to visit Taiwan, but they needed to pass through a third country before entering Taiwan.

With the Kuomintang President Ma Ying-Jeou's substantial relaxation of restrictions on Cross-Straits tourism in 2008, group-type tourism by Chinese to visit Taiwan was allowed. On 22 June 2011, the restrictions were further relaxed to allow individual-type travel to Taiwan by Chinese citizens. So far, Taiwan has allowed people in 47 cities in China to apply for individual-type travel to Taiwan, subject to a maximum number of 6000 applications per day. On 1 January 2012, Taiwan relaxed the restrictions on medical-type tourism, so that Chinese citizens could travel to Taiwan for health checks and/or for cosmetic treatments.

In the increasingly competitive tourism market, the willingness of Chinese tourists to travel in Taiwan has not only been affected by the relaxation of tourism policies across the Taiwan Strait, but also by the complicated and close Cross-Straits political relationship and concerns over tourism safety in Taiwan. The occurrence of political events and disasters or accidents have had, and will continue to have, a huge impact on the Taiwan tourism market, although so far, there has been relatively little empirical research conducted on this issue.

For this reason, this paper uses Chinese tourists as the major focus of its analysis to examine whether or not major events that have taken place on both sides of the Strait in the past three years have given rise to abnormal changes in the number of visitors to Taiwan. Moreover, the paper compares the reactions of the group-type, individual-type, and medical-type tourists to these major events.

The important events are divided into political events and disasters/accidents, and tourists are characterized as being involved in one of three types of tourism: group tourism (group-type), individual tourism (individual-type), and medical cosmetology (medical-type). First, we use McAleer's [1] fundamental equation in tourism finance to examine the correlation that exists between the rate of change in the number of tourists, and the rate of return on tourism. Second, we use the event study method to observe whether the numbers of tourists have changed abnormally before and after the occurrence of major events on both sides of the Strait.

With regard to the estimation method used to calculate the abnormal changes in the numbers of tourists, in addition to using the Ordinary Least squares (OLS) method that is most commonly used in the historical literature, we also consider the rate of change in the number of tourists and the time-varying variance in the residuals. To this end, we use three different types of conditional variance models, namely Generalized Autoregressive Conditional Heteroscedasticity, GARCH (1,1), Glosten, Jagannathan and Runkle, GJR (1,1) and Exponential GARCH, EGARCH (1,1), to estimate the abnormal rate of change in the number of tourists. In this way, we intend to obtain a more accurate estimate of the abnormal rate of change in the number of tourists.

The empirical results concerning the major events affecting the changes in the numbers of tourists from China to Taiwan are economically significant, and they confirm which types of tourists are more likely to be affected by such major events. These results can serve as a valuable reference to the Taiwan government, and to public and private policy-makers as they formulate new economic and financial tourism policies in the future.

The remainder of the paper is organized as follows. In Section 2, the background and literature are reviewed. In Section 3, the empirical models are presented. The data and variables are described in Section 4. In Section 5, the empirical results are analyzed. Some concluding comments are given in Section 6.

2. Background and Literature

It can be difficult to assess the demand for events in tourist destinations. In the following section, we break down the major events of both a political nature, as well as disasters and accidents, to focus our attention on windows in time that are easier to analyze on an individual basis.

2.1. Identifying the Cross-Strait Events in 2014–2016

Changes in Cross-Straits political stances and the environment may bring about abnormal changes in the numbers of tourists visiting Taiwan. The political orientation has always been an important event that has plagued the authorities on both sides, especially with the constant strengthening of the subjective consciousness of the Taiwanese and the united consciousness of the mainland Chinese, which has led to an extremely sensitive relationship between the two. After the Kuomintang's presidential candidate Ma Ying-Jeou took office in 2008, the "1992 Consensus, according to which both sides recognize that there is only one China, but have different opinions on what that means" (The "1992 Consensus, where both sides recognize only one China, but have different opinions", developed through the mutual non-recognition of sovereignty, mutual non-denial of each other's jurisdiction, and reciprocity and mutual benefit), was used in the institutionalized consultations between the two sides, in the hope that peaceful and stable development between the two could be maintained.

However, in 2016 there was a switch in the ruling party in Taiwan, with the election of the Democratic Progressive Party's candidate, Tsai Ing-Wen, as the Republic of China's 14th President. While it was still hoped that the peaceful and stable development of the two sides of the Straits would be maintained, in her inaugural presidential speech, President Tsai did not mention the one-China principle, thereby causing China to feel dissatisfied, and the Cross-Straits political relationship was once again affected.

A summary of the important political events that occurred on the two sides of the Taiwan Strait over the 2014–2016 period is provided below. These are also presented in Table 1.

18 March 2014–10 April 2014–The Sunflower Youth Movement: The social movement that resulted in the occupation of the Taiwan legislature by students was mainly in response to the opposition to the Kuomintang's forced passing of the review by the committee on the Cross-Straits Agreement on Trade in Services. This led to the formation of a social movement that resulted in the occupation of the Legislative Yuan by Taiwanese students and various civic groups. This event attracted the attention of people from all walks of life, and also impacted the implementation of various Cross-Straits agreements.

Table 1. Literature review of event studies.

Disaster and Accident Events		
Mazzocchi and Montini (2001)	26 September 1997	Magnitude 5.9 earthquake in Umbria (Italy)
Tao (2014)	20 April 2013	Magnitude 7.0 earthquake in Lushan (China)
Chen et al. (2007)	22 April 2003	SARS (Severe Acute Respiratory Syndrome) in Taiwan
Political Events		
Johnson et al. (2015)	4 March 2010	Travel Promotion Act of 2000
Economic Events		
Nicolau (2002)	1997–1999	New hotel openings announcement in Spain
Szutowski and Bednarska (2014)		Innovation announcement from tourism enterprises in Poland
International Competitions		
Dick and Wang (2010)	1988–2014	The Olympic Games announcement
Ogawa (2017)	9 September 2013	Tokyo 2020 Summer Olympic Games announcement

29 November 2014—Taiwan's nine-in-one local elections: These were the largest local elections for public officials in Taiwan's political history. The Kuomintang (KMT) won six seats (compared to the 15 seats it held before the election), while the Democratic Progressive Party (DPP) won 13 seats (compared to the six seats it held before the election), and independent candidates won three seats. The KMT (the ruling party) suffered an unprecedented defeat, and former president Ma Ying-jeou resigned as chairman of the KMT. This election outcome had a short-term impact on Cross-Straits relations.

7 November 2015—Ma-Xi Summit: The top leaders of Taiwan and China met at the Shangri-La Hotel in Singapore for the first time since the two sides of the Taiwan Strait became politically separated in 1949. Although the two sides did not sign an agreement or issue a joint statement, the meeting nevertheless constituted a major breakthrough in Cross-Straits relations.

16 January 2016—Taiwan's 14th presidential election and Taiwan's ninth legislative election: In Taiwan's third political party rotation, with Tsai Ing-wen being elected as Taiwan's 14th President, the DPP took charge of the executive administration and controlled over half the seats in the Legislative Yuan, a symbol of the Democratic Progressive Party being totally in power.

20 May 2016—Taiwan 14th Presidential inauguration: At her inauguration ceremony as Taiwan's 14th President, while Tsai Ing-wen advocated the maintenance of goodwill and peace across the Taiwan Strait, she did not clearly express the one-China principle, which again caused China to feel dissatisfied, thereby leading to a stalemate in Cross-Strait relations. As rumors that Chinese officials were setting limits on the numbers of Chinese tourists that would be allowed to visit Taiwan continued to spread, the willingness of Chinese tourists to visit Taiwan was indirectly affected.

18 September 2016—Taiwan mayors visit China: This was a visit by the mayors of eight counties and cities in Taiwan to Beijing to support the cooperation and exchange event to promote "China's eight measures to benefit Taiwan".

In addition to unavoidable natural disasters, tourism safety is also one of the factors that affects tourists' decisions regarding whether or not to visit a country or region. According to the Ministry of Transportation and Communications of the Republic of China, since 2008 when Taiwan relaxed restrictions to allow Chinese tourists to fly directly to and from Taiwan, 90 Chinese tourists have been killed and 390 injured in Taiwan. The following is a list of the major accidents on the two sides of the Strait between 2014 and 2016.

31 July 2014—The Kaohsiung Petrochemical gas explosion: This caused serious damage to a number of important roads in Kaohsiung, and resulted in 32 deaths and 321 people injured.

4 September 2014—Taiwan's "gutter oil" scandal: Illegal use by manufacturers of inferior-quality oil products: Taiwan's food safety issues caught the attention of the Chinese government. By immediately going through "Cross-Strait food safety agreement" channels, a comprehensive survey of food products imported into Taiwan has been conducted to maintain food safety.

6 February 2016—Kaohsiung's magnitude 6.6 Meinong earthquake: This resulted in 117 deaths and 551 people injured. The Yongkang District of Tainan suffered the most serious casualties (a total of 115 deaths), with the collapse of a large residential building. In addition, the frequency of the aftershocks following the incident resulted in increased uncertainty regarding the safety of tourists.

1 July 2016—95th Anniversary of the founding of the Communist Party of China: In commemoration of this special day, in the morning of that day, as the Taiwan Navy was conducting training operations, it accidentally fired a Hsiung Feng series 3 anti-ship missile, which resulted in the captain of a Kaohsiung fishing boat being killed and three of his crew members injured. The Taiwan government stressed that this unfortunate incident was due to negligence on the part of staff, and not political factors. This event added to the tensions between the two sides.

During the period 2014–2016, there were two major accidents involving transportation, the first being the crash of TransAsia Airways Flight No. 235 that took place on 4 February 2015; the plane came down in Taipei City, plunging into the Keelung River and killing 43 people, of whom 28 were Chinese tourists. The second major incident took place on 19 July 2016, when a tour bus, in which a tour group from Liaoning in China was travelling, struck a roadside guardrail on the way to Taoyuan Airport and immediately burst into flames, leaving a total of 26 dead.

In summary, over the 2014–2016 period, there were six important political events and disasters/accidents that occurred in Taiwan and China. These important events during 2014–2016 are listed chronologically in Figure 2.

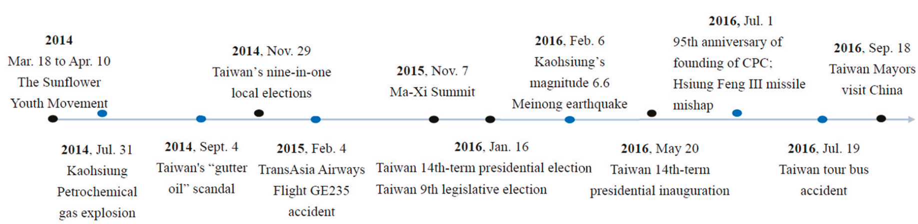


Figure 2. Major Cross-Strait events, 2014–2016.

2.2. Literature Review of Event Studies

The event study method dates back to 1933, when Dolley [2] studied the impact of stock segmentation on stock prices. The approach was subsequently widely used in the fields of economics, finance, and accounting (Ball and Brown [3]; Fama et al. [4]; Fama [5]; Boehmer et al. [6]; MacKinlay [7]; Binder [8]; Corrado [9]). The event study method has also been used in tourism research. A summary of the literature on the application of the event study approach to tourism-related issues is provided below.

Mazzocchi and Montini [10] examined the impact of the 26 September 1997 magnitude 5.9 earthquake on the flow of tourists in the Umbria region of central Italy using the event study approach. They used data covering the period January 1988–July 1998, with a particular focus on the months in which visits by tourists stopped, in order to analyze the impact of the earthquake on tourists' total number of visits. In estimation, OLS was used to estimate the average number of visits by tourists, and Patell's [11] standardized residual test was applied to estimate any abnormal changes in the number of these visits. The empirical results showed that the earthquake had a significant abnormal impact on the numbers of visits by both local tourists and foreign tourists. The number of visits by local tourists decreased by more than that for foreign tourists. In a comparison of local tourists with foreign tourists in terms of the economic losses brought about by the earthquake, for domestic tourists, the economic losses were also greater than for foreign tourists, amounting to as much as US$ 5.19 million.

Tao [12] used the event study method to study the economic impact on China's stock market of the magnitude-7.0 earthquake that occurred on 20 April 2013 in Lushan, Sichuan Province, China. The daily trading data for the China stock market included the Shanghai Composite Index, the Shenzhen Component Index, and the CSI 300 Index. Using data covering the period 20 April 2012–19 April 2013, Tao analyzed the impact of the Lushan earthquake on stock market returns. He used OLS to estimate the expected average abnormal returns, and the t-statistic to inspect the abnormal returns. The empirical results showed that the Lushan earthquake did not significantly impact the stock returns of the Shanghai Composite Index, the Shenzhen Component Index, or the CSI 300 Index. Tao attributed the reason for this to the fact that the region where the earthquake struck was not developed, and hence the impact on the economic benefits was not significant.

Nicolau [13] used the event study method to examine the impact of a hotel's announcement that it was opening for business on the stock price returns in the hotel industry. The stock prices and IBEX-35 index daily trading data for 42 newly-opened hotels listed on the Spanish Stock Exchange located in Madrid from 1997–1999 were analyzed. The GARCH(1,1) model was used to estimate the average abnormal stock returns, and Boehmer et al.'s [6] standardized cross-sectional method and Corrado's [14] non-parametric test were used to test the abnormal returns resulting from the changes in stocks. The empirical results showed that the hotel's announcement that it was opening for business had a significantly positive impact on the hotel's stock price on the day, in 61.9% of the cases.

Chen et al. [15] used the event study approach to examine the impact of the outbreak of SARS (Severe Acute Respiratory Syndrome) on the stock prices of publicly-traded hotel stock. Using the period 2 May 2002–7 April 2003 for estimation, attention was particularly focused on the 10 days and 20 days prior to and after the event date of 22 April 2003. The study used OLS, GARCH(1,1), GJR(1,1) and EGARCH(1,1) to estimate the accumulated average abnormal returns. The empirical results showed that the outbreak of the SARS epidemic after the Taiwan hotel stock price compensation had a significantly negative impact on hotel stock price returns in Taiwan.

Dick and Wang [16] used the event study method to examine the impact of announcements made by the International Olympic Committee (IOC), on which cities would host the games, on the major stock index returns of the winning and losing countries. Data covering the period 1988–2014 in relation to 15 announcements as to which countries would host future Olympic Games were used in the event study. OLS was applied to estimate the cumulative average abnormal returns, and the t-statistic was used to inspect the abnormal returns. The empirical results showed that the announcements regarding the cities that had been selected to host the Olympic Games indicated that the cumulative average abnormal returns of the stock indexes in those countries in which the cities that had placed first in the selection process had increased by about 2%, while the stock index returns of those countries that were ranked last were not significantly affected. Announcements regarding the selection as to which cities would host the Winter Olympics also did not have a significant impact on the respective countries' stock returns.

Ogawa [17] used the event study approach to analyze the impact of large-scale sporting activities on the yields of Japanese Real Estate Investment Trusts (J-REITs). Data were used for a total of 41 J-REITs quoted on the Tokyo Stock Exchange with 18 July 2013–8 September 2013 as the estimation period (there being 37 trading days after holidays were excluded), and 9 September 2013 was regarded as the event date. OLS was used to estimate the average abnormal returns, and the t-statistic was used to examine the abnormal returns. The empirical results showed that Japan's winning the bid to be selected to host the 2020 Olympic Games had both a positive and significant impact on the overall returns to real estate stocks, and the effect on J-REITs, with a particular emphasis on hotels in terms of average abnormal returns, was relatively large.

Szutowski and Bednarska [18] applied the event study method to examine the impact of tourism business announcements on stock market value. Stock price data obtained from the Warsaw Stock Exchange (WSE) and 34 innovative news reports and seven innovative types in the last six years were used in conducting the analysis. The estimation period was set to cover 250 days before the event, and the event period was established as covering 10 days before and 10 days after the announcement. OLS was used to estimate the cumulative average abnormal returns, and the Szyszka [19] J-statistic was used to check the abnormal returns. The empirical results showed that the impact of the innovative announcements by the tourism businesses on the stock market abnormal returns was 0.63%, and the cumulative average abnormal returns reached 2% during the five days before and 5 days after the announcement was made.

Johnson et al. [20] used the event study method to examine the impact of the Travel Promotion Act (TPA) of 2000 on stock price returns. They used data obtained from the Center for Research in Security Prices (CRSP), and for Real Estate Investment Trusts (REITs) in performing their analysis. With the estimation period covering 255 trading days in which the event date fell (4 March 2010), and an event period (which covered the day of the event, the day before the event and the day after the event), they used OLS to estimate the cumulative average abnormal returns and the z-statistic to test the cumulative average abnormal returns. The empirical results showed that the US Travel Promotion Act had a significant positive impact on the hotel industry's stock price returns. In addition, the large hotel chains were found to benefit more as a result of the TPA than smaller hotel chains.

In summary, when used in research related to tourism issues, the event study method has mainly been used to examine the impact of changes in the tourism environment on financial markets. The scope of the events considered includes the tourism natural environment (disaster and accident events), tourism cultural environment (political events, economic events, and international competitions), and tourism resources. These studies are classified according to different events, as shown in Table 1. Furthermore, the results of the studies has indicated that the changes in the tourism environment have a significant impact on both the number of tourist arrivals to a country, as well as its stock market returns. We have not found such connections in other studies.

3. Models

3.1. Defining the Event Study's Period

An event refers to new relevant information, which through its impact on stock prices determines whether it is a major event or not. Moreover, an event study as a form of empirical research is commonly used to investigate the impact of specific events in terms of abnormal returns in financial markets (MacKinlay [7], Binder [8], Corrado [9]). This method is derived from Fama's [5] efficient markets hypothesis (EMH), which posits that any financially-related information will immediately be reflected in stock prices.

The event study method is used to establish the difference between the counterfactual price that is not affected by the information, and the actual price, in order to estimate the price effect arising from the event (McWilliams and Siegel [21], Binder [8]). This paper uses the event study method to estimate the impact of Cross-Straits political and disaster-related incidents on Chinese tourists travelling to Taiwan.

When using the event study method, it is necessary to determine the event and the date on which the event first occurred (t_0), as well as the part of the estimation period that was not affected by the event ($T = t_2 - t_1 + 1$), and the event period ($W = t_4 - t_3 + 1$). The event study method does not have a set standard in terms of the period between the estimation period and the event period. From a review of the literature, it can be found that where the daily data are used, the estimation period tends to be in the range of 100 days to 300 days, while the event period is between 2 days and 121 days.

The events considered in this study include both political events and disaster-related incidents. The estimation period for political events ranges from 110 days prior to the date of the event, to 11 days before it ($t_1 = -110$ to $t_2 = -11$), and the event period ranges from 10 days before the political event to 20 days after it ($t_3 = -10$ to $t_4 = 20$). The estimation period for disaster-related incidents ranges from 100 days prior to the event to one day before it ($t_1 = -100$ to $t_2 = -1$), and the event period ranges from the date of the event to 30 days after it ($t_3 = 0$ to $t_4 = 30$). Regardless of whether the events are political or disaster-related, the estimation period is always 100 days, and the event period is 31 days, so that the period under observation covers a total of 131 days.

3.2. Fundamental Tourism Finance Equation and Tourism Financial Returns

McAleer [1] developed the fundamental tourism finance equation to connect the growth in the number of tourists and the returns on the associated tourism financial asset. The fundamental equation is used to derive the relationship between the change rate of tourist arrivals and the financial (tourism) returns, which is explained below.

Consider Equation (1), where total daily tourist expenditure, y_t, is equal to the daily total number of tourist arrivals, x_t, times the daily average expenditure by tourists, z_t, which is given by:

$$y_t = x_t \times z_t \tag{1}$$

It is argued in McAleer [1] that there is little evidence to suggest that the average daily expenditure by tourists, z_t , changes on a daily basis, so that z_t can be replaced by a constant, c, and Equation (1) can be replaced by:

$$y_t = c \times x_t$$

from which it follows that:

$$\Delta y_t = c \times \Delta x_t. \tag{2}$$

where Δ is the first difference operator. In Equation (2), Δy_t is the change in total daily tourism expenditure, and Δx_t is the change in the net daily tourist arrivals, where the net daily tourist arrivals is the total number of daily tourist arrivals minus the daily tourist departures.

Using the lagged version of Equation (1) to divide the left-hand side of Equation (2) by y_{t-1} and the right-hand side of Equation (3) by x_{t-1}, gives:

$$\frac{\Delta Y_t}{Y_{t-1}} = \frac{\Delta X_t}{X_{t-1}} \tag{3}$$

in which Equation (3) leads to the fundamental equation in tourism finance. This equation relates the growth in total daily tourism expenditure, or alternatively, the daily returns on total tourism, $\Delta y_t / y_{t-1}$, to the net daily tourist arrivals divided by the previous day's total number of tourists, $\Delta x_t / x_{t-1}$.

Equation (3) is the fundamental tourism finance equation, which shows that the changes in daily returns on total tourism are approximately equal to the net change rate in daily tourist arrivals. Therefore, we use the change rate of tourist arrivals to be the change rate of the total daily Chinese tourism expenditure for purpose of analysis.

The change rate of tourist arrivals, R_t, is given as the first difference in log arrivals, and multiplied by 100, as follows:

$$R_t = \ln(A_t / A_{t-1}) \times 100 \tag{4}$$

where A_t and A_{t-1} are the daily tourist arrivals for the time periods t and $t-1$, respectively.

3.3. Estimating the Expected Rate of Change in Tourist Arrivals

The market model of Sharpe [22], one of several risk-adjusted returns models, is used to estimate the expected rate of change in the number of Chinese tourists to Taiwan (MacKinlay [7]).

In order to estimate the expected rate of change in the number of Chinese tourists, this paper uses OLS and three frequently applied conditional volatility models, namely, GARCH (1,1), GJR (1,1), and

EGARCH (1,1), to evaluate the abnormal returns from significant events. The methods of estimation cover the standard OLS approach, whereby the conditional volatilities are constant, and the three most widely used methods, when the conditional volatilities vary dynamically over time.

3.3.1. OLS

$$\begin{gathered} R_t = \phi_1 + \phi_2 R_{mt} + \varepsilon_t,\ t \in T = [t_1, t_2] \\ E(\varepsilon_t) = 0 \\ var(\varepsilon_t) = \sigma_\varepsilon^2 \end{gathered} \quad (5)$$

where R_t is the rate of change in the number of tourists; $t = [t_1, t_2]$ refers to different time points within the estimation period; R_{mt} is the rate of change in the number of tourists in the market; ε_{it} is the error term, where $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$; ϕ_1 and ϕ_2 are regression coefficients, where ϕ_1 is the intercept, and ϕ_2 is systematic risk, referring to the sensitivity of the rate of change in the number of visits by Chinese tourists as compared to the rate of change in the number of visits by foreign tourists as a whole; T is the length (or number of periods) in the estimation period, where $T = t_2 - t_1 + 1$.

However, the classical regression model assumes that the variance of the regression error term is a fixed constant, but time series data are mostly characterized by time-varying heteroscedasticity. If OLS is used to estimate the expected rate of change in the number of Chinese tourists visiting Taiwan, the estimation is likely to be biased. To resolve this problem, Engle [23] proposed the Auto-Regressive Conditional Heteroskedasticity (ARCH) model to compensate for the changes in the time series data due to the changes in the time points, as well as for the volatility clustering and heavy tails. Given below are the regression equations for three univariate conditional volatility models that are used to estimate the expected rate of change in the number of Chinese tourists. For a more detailed derivation, the interested reader may refer to McAleer [24] and Chang et al. [25].

3.3.2. GARCH

Bollerslev [26] generalized the Auto-Regressive Conditional Heteroskedasticity (ARCH) model, and proposed the Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) model. At the same time, the concepts of the Auto-Regressive (AR) model and the Moving-Average (MA) model were used in the estimation of the conditional variance. The model uses GARCH(1,1) to construct the regression equation and conditional mean equation, as follows:

$$R_t = \phi_1 + \phi_2 R_{mt} + \varepsilon_t,\ t \in T = [t_1, t_2] \quad (6)$$

$$\begin{gathered} \varepsilon_t = \theta_t \varepsilon_{t-1} + \eta_t \\ \theta_t \sim iid(0, \alpha); \eta_t \sim iid(0, \omega) \\ \eta_t = \varepsilon_t / \sqrt{h_t} \end{gathered} \quad (7)$$

$$h_t = E(\varepsilon_{t-1}^2 | I_{t-1}) = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \quad (8)$$

where $\varepsilon_t | I_{t-1} \sim N(0, h_t)$, and I_{t-1} is the information set in period $t - 1$. The mean of the conditional distribution of the error terms is zero, the variance is h_t, and η_t is the standardized residual. In accordance with Engle's [23] ARCH(1) model, Tsay [27] obtained the ARCH(1,1) conditional variance equation as shown in Equation (8), with $\beta = 0$.

As Equation (8) shows, h_t is the conditional volatility, α is the impact of short-term persistence in the ARCH effect, and $(\alpha + \beta)$ is the impact of long-term persistence in the GARCH effect. According to McAleer [24], $\omega > 0$, $\alpha > 0$ and $\beta \in [-1, 1]$ in Equation (8), in order to satisfy the sufficient condition that $h_t > 0$. Moreover, from Equation (7), it can be seen that $\omega > 0$ and $\alpha > 0$. When the condition that $\alpha + \beta < 1$ is satisfied, this means that the quasi-maximum likelihood estimates (QMLE) of the parameters in Equation (8) satisfy the sufficient conditions for consistency and asymptotic normality (see Ling and McAleer [28]).

3.3.3. GJR

GARCH is unable to capture the asymmetric effect in financial time series data. In order to capture such asymmetry, Glosten et al. [29] proposed the Threshold or asymmetric GARCH (or GJR) model, using an indexed random variable ($I(\varepsilon_{t-1})$) to represent different conditions inside and outside the threshold variance values, so that the conditional variation value can exhibit two different phenomena. The regression equation for GJR(1,1) is as follows:

$$R_t = \phi_1 + \phi_2 R_{mt} + \varepsilon_t,\ t \in T = [t_1, t_2] \tag{9}$$

$$\begin{gathered}\varepsilon_t = \theta_t \varepsilon_{t-1} + \psi_t I(\varepsilon_{t-1}) + \eta_t \\ \theta_t \sim iid(0, \alpha);\ \psi_t \sim iid(0, \gamma);\ \eta_t \sim iid(0, \omega) \\ I(\varepsilon_{t-1}) = 1\ when\ \varepsilon_{t-1} < 0 \\ I(\varepsilon_{t-1}) = 0\ when\ \varepsilon_{t-1} \geq 0 \\ \eta_t = \varepsilon_t / \sqrt{h_t}\end{gathered} \tag{10}$$

$$h_t = E\left(\varepsilon_{t-1}^2 | I_{t-1}\right) = \omega + \alpha \varepsilon_{t-1}^2 + \gamma I(\varepsilon_{t-1})\Big) + \beta h_{t-1} \tag{11}$$

where γ is the asymmetry parameter; when $\gamma > 0$, there is an asymmetric effect inherent within the time series data. $\alpha + \gamma/2$ is the short-term impact persistence, and $\alpha + \beta + \gamma/2$ is the long-term impact persistence. As the GARCH model is nested inside the GJR model, with the exception of the asymmetry parameter (γ), the coefficients of the two models are explained in the same way. A sufficient condition for the QMLE of the parameters in GJR(1,1) to be consistent and asymptotically normal is $\alpha + \beta + \gamma/2 < 0$ (see Ling and McAleer [28]).

3.3.4. EGARCH

Nelson [30] proposed the Exponential GARCH (EGARCH) model, in which the conditional variance equation is set as a logarithmic function. The EGARCH model can capture the asymmetric effect in the time series data. The EGARCH(1,1) regression equation may be expressed as follows (for a detailed derivation, see McAleer and Hafner [31]):

$$R_t = \phi_1 + \phi_2 R_{mt} + \varepsilon_t,\ t \in T = [t_1, t_2] \tag{12}$$

$$\begin{gathered}\varepsilon_t = \theta_t \sqrt{|\eta_{t-1}|} + \psi_t \sqrt{\eta_{t-1}} + \eta_t \\ \theta_t \sim iid(0, \alpha);\ \psi_t \sim iid(0, \gamma);\ \eta_t \sim iid(0, \omega)\end{gathered} \tag{13}$$

$\sqrt{\eta_{t-1}}$ is a complex-valued function of η_{t-1}.

$$\begin{gathered}\eta_t = \varepsilon_t / \sqrt{h_t} \\ h_t = E(\varepsilon_{t-1}^2 | I_{t-1}) = \omega + \alpha |\eta_{t-1}| + \gamma \eta_{t-1} + \beta h_{t-1}\end{gathered} \tag{14}$$

$$logh_t = E(\varepsilon_{t-1}^2 | I_{t-1}) = \omega + \alpha |\eta_{t-1}| + \gamma \eta_{t-1} + \beta h_{t-1} \tag{15}$$

$logh_t = \log(1 + (h_{t-1} - 1)) \approx h_{t-1} - 1$ is an approximation used to replace h_t in Equation (14).

3.4. Calculating the Cumulative Abnormal Change Rate

By using the OLS, GARCH(1,1), GJR(1,1), and EGARCH(1,1) regression equations mentioned above, we can estimate the regression coefficients $\hat{\phi}_1$ and $\hat{\phi}_2$, respectively, and $\hat{\phi}_1$ and $\hat{\phi}_2$ can be brought into the events period data, in order to forecast the rate of change in the number of Chinese tourists visiting Taiwan, as shown in Equation (16) (see McAleer and Hafner [31]):

$$ER_E = \hat{\phi}_1 + \hat{\phi}_2 \cdot R_{mE},\ E \in W = [t_3, t_4] \tag{16}$$

where ER_E is the rate of change in the number of Chinese tourists visiting Taiwan in period E within the event period, R_{mE} is the rate of change in the total number of tourists visiting Taiwan in period E within the event period, and W is the length of the event period (the number of periods), where $W = t_4 - t_3 + 1$.

The formula used to calculate the abnormal rate of change in the number of Chinese tourists visiting Taiwan is as follows:

$$AR_E = R_E - ER_E,\ E \in W = [t_3, t_4] \tag{17}$$

where AR_E is the abnormal rate of change in the number of Chinese tourists visiting Taiwan in period E within the event period, R_E is the rate of change in the number of Chinese tourists actually visiting Taiwan in period E within the event period, and ER_E is the rate of change in the number of Chinese tourists that are expected to visit Taiwan in period E within the event period.

The cumulative abnormal change rate (CAR) is the cumulative abnormal rate of change in the number of tourists between any two periods within the event period. The formula is as follows:

$$\mathrm{CAR}(\tau_1, \tau_2) = \sum\nolimits_{E=\tau_1}^{\tau_2} AR_E,\ [\tau_1, \tau_2] \in W = [t_3, t_4] \tag{18}$$

where $\mathrm{CAR}(\tau_1, \tau_2)$ is the abnormal rate of change in the cumulative number of Chinese tourists from period τ_1 to τ_2 during the event period, and AR_E is the abnormal rate of change in the number of Chinese tourists in period E in the event period. $[\tau_1, \tau_2]$ represents a total of m periods, from periods τ_1 to τ_2 during the event period, where $m = \tau_2 - \tau_1 + 1$, and $t_4 \geq \tau_2 \geq \tau_1 \geq t_3$.

3.5. Testing the Cumulative Abnormal Change Rate

The traditional method (Brown and Warner [32]) and the standardized-residual method (Patell [11]) are used to test the cumulative abnormal change rate in terms of the number of tourists. The null (H_0) and alternative hypotheses (H_1) are as follows:

$$\begin{aligned} H_0 &: CAR(\tau_1, \tau_2) = 0 \\ H_1 &: CAR(\tau_1, \tau_2) \neq 0 \end{aligned} \tag{19}$$

The traditional method (hereafter TM) uses the residual variance in the estimation period to simulate the residual variance in the event period. This test assumes that the residual variance in the estimation period is equal to that in the event period. The event will not cause the event-induced variance in the abnormal returns to change in the event period. Moreover, the abnormal returns in the estimation period and the event period will not lead to structural change, indicating that the parameters estimated by the equation for the expected returns in the estimation period will not change in the event period. The test statistic for the cumulative abnormal change rate in terms of the number of tourists is as shown in the following equation:

$$t^{\mathrm{TM}} = \frac{CAR(\tau_1, \tau_2)}{\sqrt{Var(CAR(\tau_1, \tau_2))}} = \frac{\sum_{E=\tau_1}^{\tau_2}\left(\frac{AR_E}{\sqrt{m}}\right)}{\hat{S}_i} \tag{20}$$

where $CAR(\tau_1, \tau_2)$ is the abnormal change rate in the cumulative number of tourists from period $\tau_1$toτ_2 in the event period; $Var(CAR(\tau_1, \tau_2))$ is the variance of the abnormal change rate in the cumulative number of Chinese tourists from period $\tau_1$toτ_2 in the event period; AR_E refers to the abnormal returns of the Chinese tourists in period E in the event period; $\hat{S}$ is the standardized error of the residual for Chinese tourists in the estimation period, that is:

$$\hat{S} = \sqrt{\frac{\sum_{t=t_1}^{t_2}\left(\hat{\varepsilon}_t - \sum_{t=t_1}^{T}\frac{\hat{\varepsilon}_t}{T}\right)^2}{T-1}}$$

$\hat{\varepsilon}_t$ is the residual for Chinese tourists in period t in the estimation period, that is, $\hat{\varepsilon}_t = R_t - E(\hat{R}_t)$, where T is the length of the estimation period (the number of periods), and $T = t_2 - t_1 + 1$; and m is the length of the estimation period from period $\tau_1$toτ_2 in the event period (the number of periods), where $m = \tau_2 - \tau_1 + 1$.

The standardized-residual method (hereafter SRM) standardizes the abnormal change rate in the number of Chinese tourists, resulting in the distribution of the abnormal change rate in the number of each type of tourist being a unit-normal distribution, thereby ensuring that the abnormal change rate for the cumulative number of tourists is normally distributed. The test statistic for the abnormal change rate in the cumulative number of tourists is as shown in the following equation:

$$t^{\text{SRM}} = \frac{\text{SCAR}(\tau_1, \tau_2)}{\sqrt{Var(\text{SCAR}(\tau_1, \tau_2))}} = \frac{\sum_{E=\tau_1}^{\tau_2}\left(\frac{SAR_E}{\sqrt{m}}\right)}{\left[\frac{T-2}{T-4}\right]^{\frac{1}{2}}} \tag{21}$$

where $\text{SC}AR(\tau_1, \tau_2)$ is the abnormal rate of change in the standardized cumulative number of Chinese tourists from period $\tau_1$toτ_2 in the event period; $\text{Var}(\text{SC}AR\tau_1, \tau_2)$ is the variance of the abnormal rate of change in the standardized cumulative number of Chinese tourists from period $\tau_1$toτ_2 in the event period; SAR_E is the abnormal rate of change in the standardized cumulative number of Chinese tourists from period $\tau_1$toτ_2 in the event period. The formula used to calculate SAR_E is as follows:

$$SAR_E = \frac{AR_E}{\hat{S}\sqrt{1 + \frac{1}{T} + \frac{\left(R_{mE} - \overline{R}_{mT}\right)^2}{\sum_{t=t_1}^{t_2}\left(R_{mt} - \overline{R}_{mT}\right)^2}}} \tag{22}$$

where $\hat{S}$ is the standard deviation of the residuals for the Chinese tourists in the estimation period, as give above, $\hat{\varepsilon}_t$ is the residual for the Chinese tourists in period t in the estimation period, that is, $\hat{\varepsilon}_t = R_t - E(\hat{R}_t)$; R_{mE} is the rate of change in the total number of international travelers visiting Taiwan in period E in the event period; R_{mt} is the rate of change in the total number of international travelers visiting Taiwan in period t in the estimation period; $\overline{R}_{mT}$ is the mean of the rate of change in the total number of international travelers visiting Taiwan in period T in the estimation period, that is, $\overline{R}_{mT} = \frac{1}{T}\sum_{t=t_1}^{t_2} R_{mt}$; T is the length of the estimation period (number of periods), that is, $T = t_2 - t_1 + 1$. In addition, because of the differences in the data, which lead to the observed values of T in each sample period being likely to be different, the expected value of SAR_E is equal to zero, and the variance is $(T-2)/(T-4)$. Therefore, the standardized cumulative abnormal rate of change is $\text{SC}AR(\tau_1, \tau_2) = \sum_{E=\tau_1}^{\tau_2} SAR_E$. Moreover, the variance of the standardized cumulative abnormal change rate in the number of tourists is $Var(\text{SC}AR(\tau_1, \tau_2)) = m\left(\frac{T-2}{T-4}\right)$, where m is the length of that part of the event period from period $\tau_1$toτ_2 (number of periods), that is, $m = \tau_2 - \tau_1 + 1$.

In summary, the paper uses the traditional method and the standardized residual method to test the cumulative abnormal rate of change in the number of tourists in the event period. If the test statistic rejects the null hypothesis (H_0), this indicates that abnormal change arising from the event is present.

4. Data and Variables

The data set comprises daily tourist arrivals from the world and China to Taiwan for the period 1 January 2014 to 31 October 2016, giving 1035 observations that are obtained from the National Immigration Agency of Taiwan (Taiwan Tourism Bureau, Statistic Data, Retrieved 17 June 2017 from http://admin.taiwan.net.tw/ (in Chinese).

The data were collected by the National Immigration Agency of Taiwan. The original data source comprises daily tourist arrivals from the world and China to Taiwan for the period from 1 January 2014 to 31 October 2016, giving 1035 observations. Based on the original data source from the National

Immigration Agency of Taiwan, we can disaggregate three types of Chinese tourists to Taiwan, namely Group-type, Individual-type, and Medical-type.

We have selected several of the most important political events, and disaster and accident events, based on public news that highlighted the important events at the time. Given the limitations in obtaining data from the National Immigration Agency in Taiwan, we focus on three different types of Chinese visitors: (1) Group type, (2) Individual type, and (3) Medical type. Figure 3 presents the trend for international tourists and for the three types of Chinese tourists to Taiwan.

The paper examines the effect of six political events and six disaster and accident events on the change rate of Chinese tourist arrivals to Taiwan, using an event study approach. The explanations of each major Cross-Strait event and sample period are given below. Table 2 presents the time period corresponding to each event.

Table 2. Major cross-strait events and sample periods.

	Notation	Event	Event Date T = 0	Sample Period	
				Estimation Period $[t_1, t_2]$	**Event Period** $[t_3, t_4]$
Political events	Case I	The Sunflower Youth Movement	18 March 2014	2 January 2014–17 March 2014	18 March 2014–17 April 2014
	Case II	Taiwan's nine-in-one local elections	29 November 2014	11 August 2014–18 November 2014	19 November 2014–19 December 2014
	Case III	Ma-Xi Summit	7 November 2015	20 July 2015–27 October 2015	28 October 2015–27 November 2015
	Case IV	Taiwan 14th-term presidential election and Taiwan ninth legislative election	16 January 2016	28 September 2015–5 January 2016	6 January 2016–5 February 2016
	Case V	Taiwan 14th-term presidential inauguration	20 May 2016	31 January 2016–9 May 2016	10 May 2016–9 June 2016
	Case VI	Taiwan mayors visit China	18 September 2016	31 May 2016–7 September 2016	8 September 2016–8 October 2016
Disaster and accident events	Case VII	The Kaohsiung Petrochemical gas explosion	31 July 2014	22 April 2014–30 July 2014	31 July 2014–30 August 2014
	Case VIII	Taiwan's "gutter oil" scandal	4 September 2014	27 May 2014–3 September 2014	4 September 2014–4 October 2014
	Case IX	TransAsia Airways Flight GE235 accident	4 February 2015	27 October 2014–3 February 2015	4 February 2015–6 March 2015
	Case X	Kaohsiung's magnitude 6.6 Meinong earthquake	6 February 2016	29 October 2015–5 February 2016	6 February 2016–7 March 2016
	Case XI	95th anniversary of the founding of the Communist Party of China (CPC) and the Hsiung Feng III missile mishap	1 July 2016	23 March 2016–30 June 2016	1 July 2016–31 July 2016
	Case XII	Taiwan tour bus accident	19 July 2016	10 April 2016–18 July 2016	19 July 2016–18 August 2016

(1) Political Events

Case I: The Sunflower Youth Movement
Event date (t = 0): 18 March 2014
Estimation period: 2 January 2014–17 March 2014 (75 days)
Event period ($\tau_1 = 0, \tau_2 = 30$): 18 March 2014–17 April 2014 (31 days)

Case II: Taiwan's nine-in-one local elections
Event date (t = 0): 29 November 2014
Estimation period: 8 November 2014–18 November 2014 (100 days)
Event period ($\tau_1 = -10,\ \tau_2 = 20$): 19 November 2014–19 December 2014 (31 days)

Case III: Ma-Xi Summit
Event date (t = 0): 7 November 2015

Estimation period: 20 July 2015–27 October 2015 (100 days)
Event period ($\tau_1 = -10,\ \tau_2 = 20$): 28 October 2015–27 November 2015 (31 days)

Case IV: Taiwan 14th presidential election and Taiwan ninth legislative election
Event date (t = 0): 16 January 2016
Estimation period: 28 September 2015–5 January 2016 (100 days)
Event period ($\tau_1 = -10,\ \tau_2 = 20$): 6 January 2016–5 February 2016 (31 days)

Case V: Taiwan 14th Presidential inauguration
Event date (t = 0): 20 May 2016
Estimation period: 31 January 2016–9 May 2016 (100 days)
Event period ($\tau_1 = -10,\ \tau_2 = 20$): 10 May 2016–9 June 2016 (31 days)

Case VI: Taiwan mayors visit China
Event date (t = 0): 18 September 2016
Estimation period: 31 May 2016–7 September 2016 (100 days)
Event period ($\tau_1 = -10,\ \tau_2 = 20$): 8 September 2016–8 October 2016 (31 days)

(2) Disaster and Accident Events

Case VII: The Kaohsiung Petrochemical gas explosion
Event date (t = 0): 31 July 2014
Estimation period: 22 April 2014–30 July 2014 (100 days)
Event period ($\tau_1 = 0, \tau_2 = 30$): 31 July 2014–30 August 2014 (31 days)

Case VIII: Taiwan's "gutter oil" scandal
Event date (t = 0): 4 September 2014
Estimation period: 27 May 2014–3 September 2014 (100 days)
Event period ($\tau_1 = 0, \tau_2 = 30$): 4 September 2014–4 October 2014 (31 days)

Case IX: TransAsia Airways Flight GE235 accident
Event date (t = 0): 4 February 2015
Estimation period: 27 October 2014–3 February 2015 (100 days)
Event period ($\tau_1 = 0, \tau_2 = 30$): 4 February 2015–6 March 2015 (31 days)

Case X: Kaohsiung's magnitude 6.6 Meinong earthquake
Event date (t = 0): 6 February 2016
Estimation period: 29 October 2015–5 February 2016 (100 days)
Event period ($\tau_1 = 0, \tau_2 = 30$): 6 February 2016–7 March 2016 (31 days)

Case XI: 95th anniversary of the founding of the Communist Party of China and the Hsiung Feng III missile mishap
Event date (t = 0): 1 July 2016
Estimation period: 23 March 2016–30 June 2016 (100 days)
Event period ($\tau_1 = 0, \tau_2 = 30$): 1 July 2016–31 July 2016 (31 days)

Case XII: Taiwan tour bus accident
Event date (t = 0): 19 July 2016
Estimation period: 10 April 2016–18 July 2016 (100 days)
Event period ($\tau_1 = 0, \tau_2 = 30$): 19 July 2016–18 August 2016 (31 days)

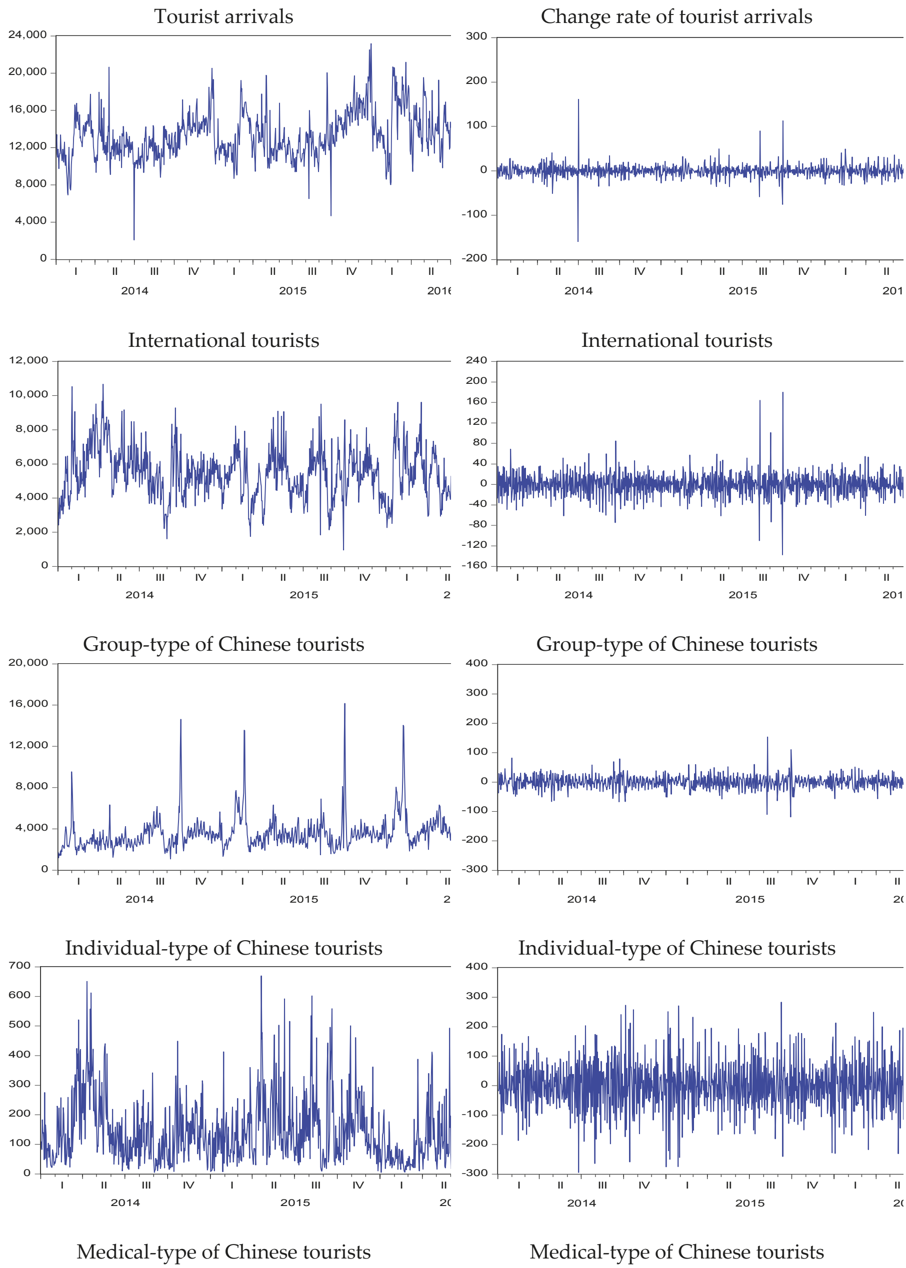


Figure 3. Daily tourist arrivals to Taiwan, 1/1/2014–31/10/2016

5. Empirical Results

As discussed previously, in this section we use the OLS, GARCH (1,1), GJR (1,1), and EGARCH (1,1) models to estimate the expected number of tourists during the event periods, and we use the difference between the expected number of tourists and the actual number of tourists to calculate the average abnormal rate of change and cumulative abnormal rate of change. We extend the analysis to use the traditional method (Brown and Warner [32]) and the standardized residual method (Patell [11]) to determine whether there are abnormal changes in the cumulative numbers of Chinese tourists visiting Taiwan, due to the occurrence of each event in Table 3. For the detailed results of the estimation by OLS, GARCH, GJR, and EGARCH, refer to Tables A1–A48 (in Appendix A). The trend for the cumulative rate of change in the number of tourists is given in Figure 4.

The empirical results can and do differ according to the different political events, and different disasters and accident events, as well as with the different methods of estimation. In order to provide a comprehensive analysis of each type of event, as estimated by alternative methods, a detailed analysis of each combination is required.

The Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests are used to determine whether the data for the rate of change in the number of tourists are stationary. As shown in Table 4, the series for the rate of change in the number of Chinese tourists visiting Taiwan is stationary. The empirical results regarding the tests that were carried out to determine whether the returns to Chinese tourists visiting Taiwan are abnormally affected by the political and disaster-related events are listed sequentially.

Table 3. Results for cumulative abnormal change rate of Chinese tourist arrivals.

Political Events									
Event	**Types**	**OLS**		**GARCH(1,1)**		**GJR(1,1)**		**EGARCH(1,1)**	
		TM	**SRM**	**TM**	**SRM**	**TM**	**SRM**	**TM**	**SRM**
	Group								
Case I	Individual								
	Medical								
	Group								
Case II	Individual								
	Medical								
	Group								
Case III	Individual								
	Medical								
	Group	+	+	+	+	+	+	+	+
Case IV	Individual	+	+	+	+				
	Medical								
	Group	-	-						
Case V	Individual								
	Medical								
	Group	+	+	+	+				
Case VI	Individual	+	+	+	+	+	+	+	+
	Medical	-	-						
Disaster and Accident Events									
Event	**Types**	**OLS**		**GARCH(1,1)**		**GJR(1,1)**		**EGARCH(1,1)**	
		TM	**SRM**	**TM**	**SRM**	**TM**	**SRM**	**TM**	**SRM**
	Group	-	-	-	-	-	-		
Case VII	Individual	-	-	-	-	-	-	-	-
	Medical	+	+	+	+	+	+		
	Group	+	+	+	+	+	+	+	+
Case VIII	Individual	+	+	+	+	+	+	+	+
	Medical	+	+						

Table 3. *Cont.*

Disaster and Accident Events									
Event	**Types**	**OLS**		**GARCH(1,1)**		**GJR(1,1)**		**EGARCH(1,1)**	
		TM	**SRM**	**TM**	**SRM**	**TM**	**SRM**	**TM**	**SRM**
Case IX	Group	-	-	-	-	-	-	-	-
	Individual	-	-	-	-	-	-	-	-
	Medical	-	-	-	-				
Case X	Group								
	Individual	-	-	-	-	-	-		
	Medical	-	-			-	-		
Case XI	Group								
	Individual								
	Medical								
Case XII	Group								
	Individual								
	Medical								

Notes: (1) Traditional method (TM) is the traditional method proposed by Brown and Warner [32]. (2) SRM is the standardized-residual method proposed by Pattel [11]. (3) - and + denote that the cumulative change rate of Chinese tourist arrivals are negative abnormal and positive abnormal, respectively.

Table 4. Unit root tests.

Variables		**Augmented Dickey-Fuller (ADF) Test**		
		No Trend and Intercept	**With Intercept**	**With Trend and Intercept**
International tourists		−20.34 *	−20.34 *	−20.33 *
Chinese tourists	Group-type	−14.90 *	−14.90 *	−14.90 *
	Individual-type	−15.24 *	−15.23 *	−15.24 *
	Medical-type	−19.54 *	−19.53 *	−19.52 *
Variables		**PP test**		
		No Trend and Intercept	**With Intercept**	**With Trend and Intercept**
International tourists		−151.73 *	−151.95 *	−151.94 *
Chinese tourists	Group-type	−111.90 *	−112.66 *	−124.12 *
	Individual-type	−79.35 *	−79.27 *	−80.91 *
	Medical-type	−284.46 *	−307.89 *	−377.68 *

Note: * denotes significant at the 1% level.

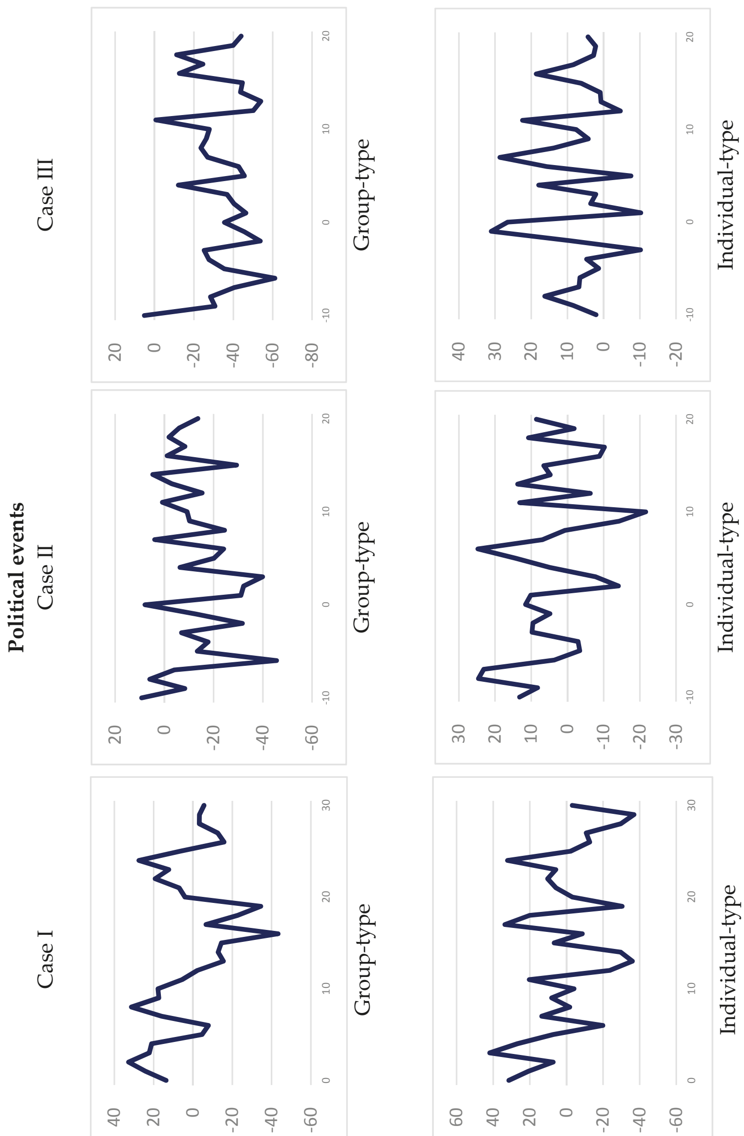


Figure 4. *Cont.*

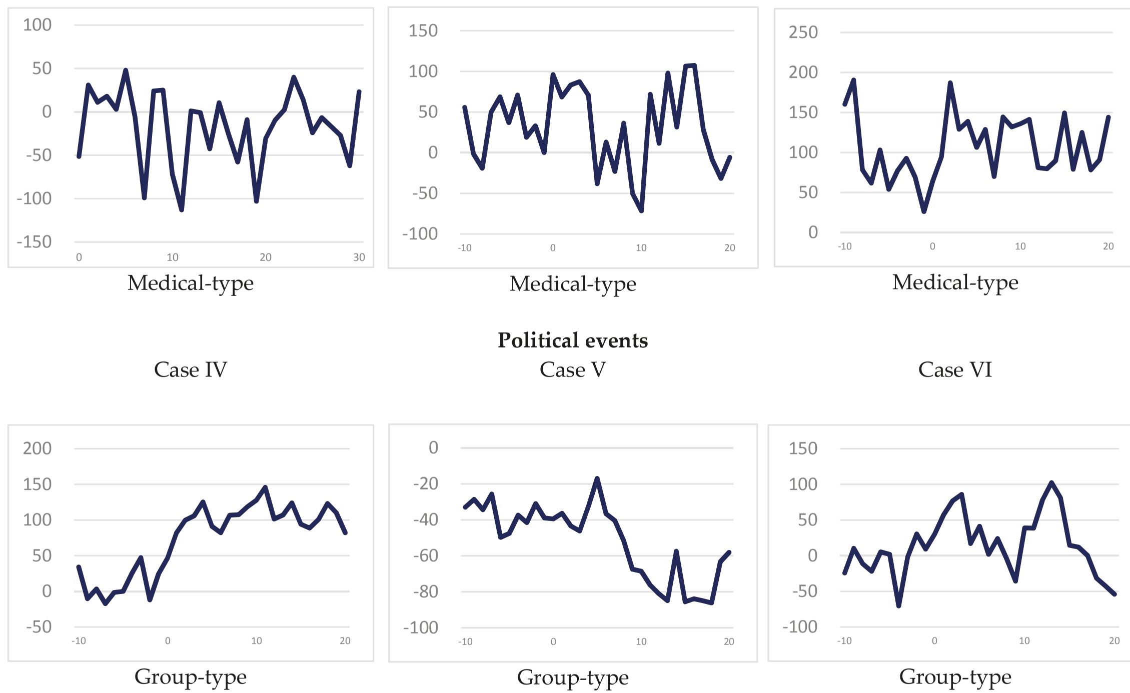
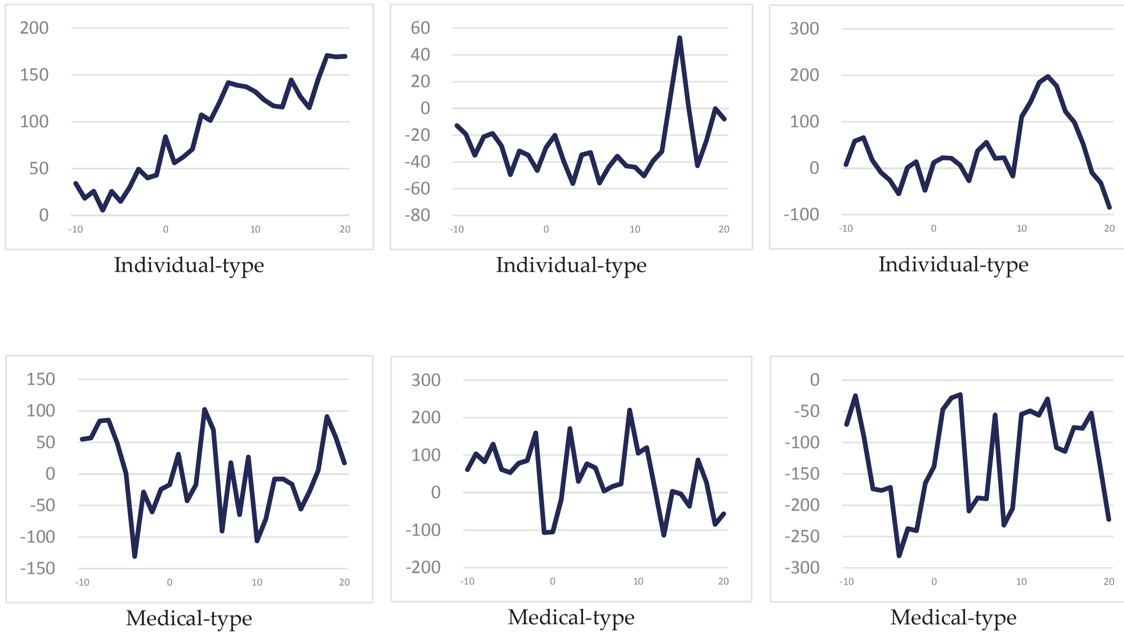


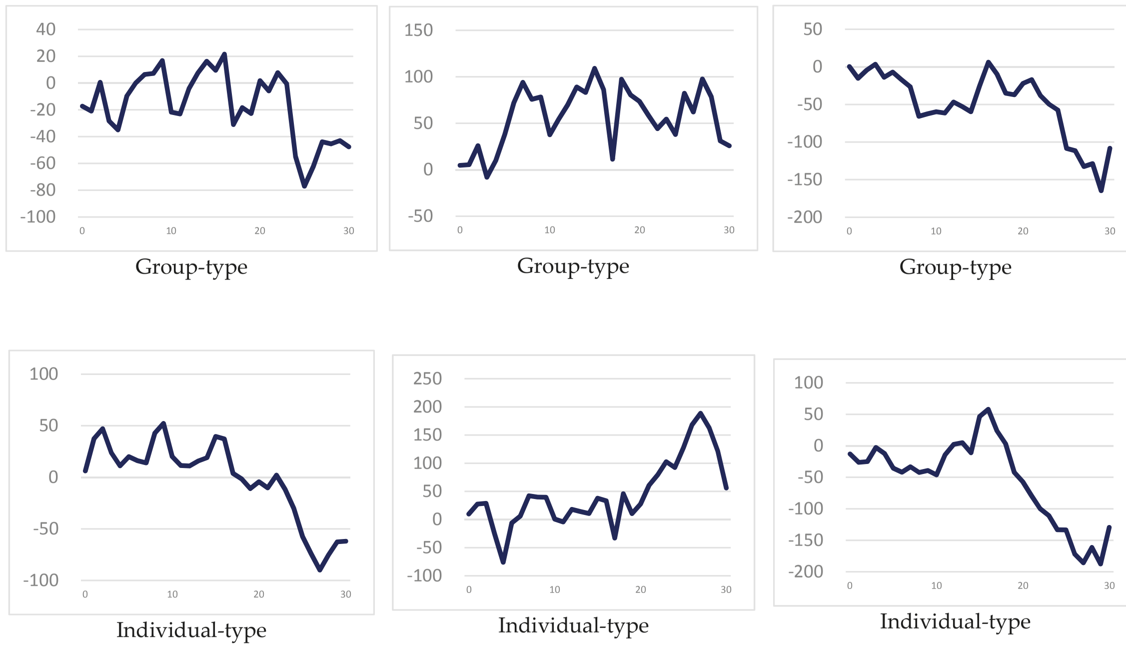
Figure 4. *Cont.*



Disaster and Accident Events

Case VII Case VIII Case IX

Figure 4. *Cont.*



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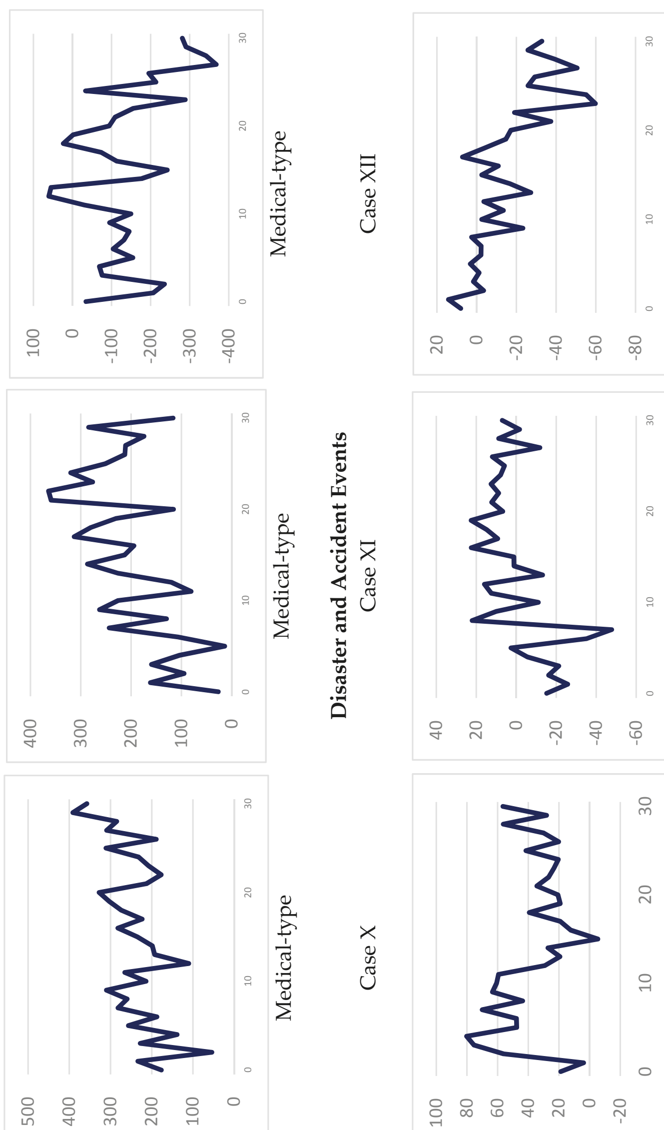

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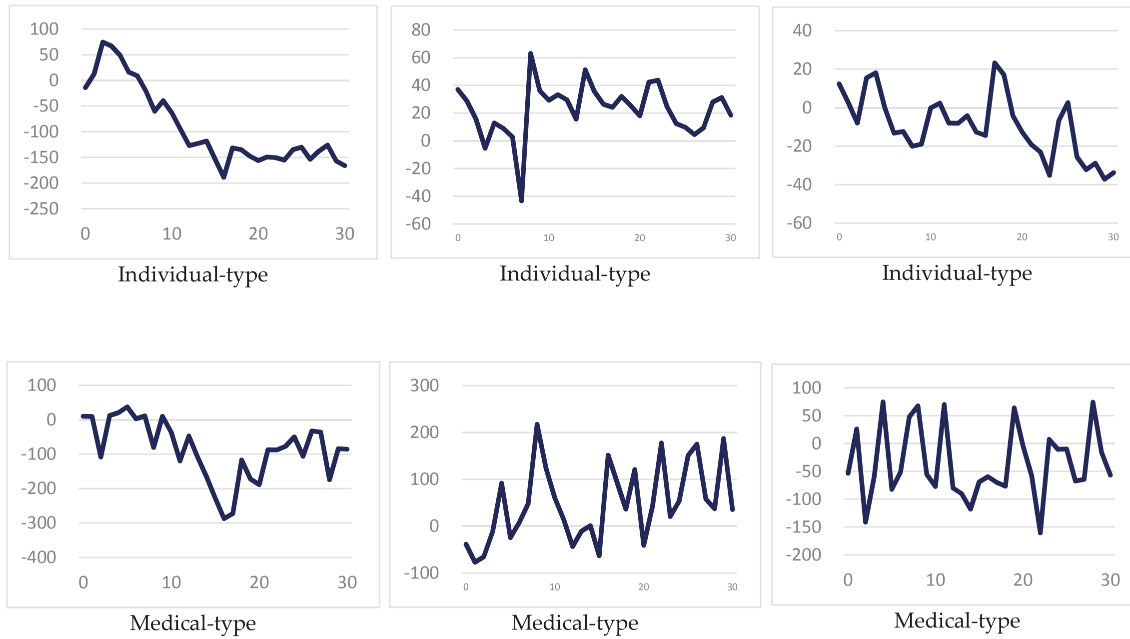

Figure 4. Cumulative abnormal change rate of Chinese tourist arrivals to Taiwan.

5.1. Empirical Results for Political Events

(1) Case I: The Sunflower Youth Movement

Although the Sunflower movement, which resulted in students and civic groups occupying Taiwan's Legislative Yuan for half a month, raised concerns from people in all walks of life and impacted the implementation of various Cross-Strait agreements, the empirical results did not reveal any significant changes in the number of each group of Chinese tourists visiting Taiwan. For the detailed results of the model parameter estimation, see Tables A1–A4.

The cumulative abnormal change rate (CAR) for three types of Chinese tourist arrivals to Taiwan are given according to four estimation methods, namely OLS, GARCH, GJR, and EGARCH. The empirical results are consistent in that there are no significant factors for any group of Chinese tourist arrivals to Taiwan, regardless of whether the traditional or standardized-residual method is used.

(2) Case II: Taiwan's nine-in-one local elections

Taiwan's nine-in-one local elections that were held in 2014 resulted in the Kuomintang (KMT) suffering an unprecedented defeat; as a consequence, the former President Ma Ying-jeou resigned as chairman of the KMT party. Although there was much public concern as to what impact the election results might have on future Cross-Straits relationship, the two sides continued to maintain friendly and interactive relations. The empirical results do not show that there was a significant abnormal change in the number of each group of Chinese tourists visiting Taiwan. For the detailed results of the parameter estimation, see Tables A5–A8.

The CAR for three types of Chinese tourist arrivals to Taiwan are given according to four estimation methods. The empirical results are consistent, in that there are no significant factors for any group of Chinese tourist arrivals to Taiwan, regardless of whether the traditional or standardized-residual method is used.

(3) Case III: Ma-Xi Summit

For the first time since the political separation in 1949 between the two sides of the Taiwan Strait, the top leaders of Taiwan and China met in Singapore. Although the meeting symbolized a major breakthrough in Cross-Strait relations, the two sides did not sign an agreement or issue a joint statement. For this reason, the empirical results did not exhibit a significant abnormal change in the number of each group of Chinese tourists visiting Taiwan. See Tables A9–A12 for the detailed results of the model estimation.

The CAR for three types of Chinese tourist arrivals to Taiwan are given according to four estimation methods. As in Cases I and II, the empirical results are consistent in that there are no significant factors for any group of Chinese tourist arrivals to Taiwan, regardless of whether the traditional or standardized-residual method is used.

(4) Case IV: Taiwan 14th Presidential election and Taiwan ninth legislative election

President Tsai Ing-wen's speech on 4 June 2015, prior to the presidential election and the 12 December 2015 subsequent political statements made on 22 December 2015, stated that the status quo would be maintained in the Cross-Strait relationship, and that good Cross-Strait interactions and goodwill would also continue. The results for all models show that there was a significant abnormal increase in the number of Group-type tourists from China after the event took place, and the results of OLS and GARCH (1,1) estimation indicate that the number of Individual-type tourists from China also increased abnormally after the event. The Medical-type tourists from China did not, however, experience any abnormal changes. These results show that the number of both Group-type and Individual-type tourists increased abnormally (with + effects) after the Taiwan 14th Presidential election and the Taiwan ninth legislative election. However, Medical-type tourists do not seem to have been affected by this event. See Tables A13–A16 for the detailed results of the model estimation.

These empirical results are important as they show that CAR varies according to the type of Chinese tourists, as well as the method of estimation, and whether the traditional or standardized-residual method is used.

(5) Case V: Taiwan 14th Presidential inauguration

OLS estimates showed that the number of Group-type tourists significantly and abnormally declined following the incident, but the numbers of Individual-type and Medical-type tourists did not experience any abnormal changes. As President Tsai Ing-wen did not mention the 1992 Consensus in her inaugural address, the Chinese government expressed dissatisfaction and Cross-Strait relations stalled, affecting interactions between the two sides. It was rumored that the Chinese government had decided to limit the numbers of Group-type tourists visiting Taiwan. The empirical results confirm the above statements. However, the numbers of Individual-type tourists visiting Taiwan did not decline abnormally. Since the quality of Taiwan's medical treatment is high and its cost is low, the numbers of Medical-type tourists, who mainly come to Taiwan for medical check-ups or cosmetic treatments, were not affected by the political events. See Tables A17–A20 for the detailed results of the model estimation.

The CAR for three types of Chinese tourist arrivals to Taiwan are given, according to four estimation methods. As in Cases I, II, and III, the empirical results are consistent in that there are no significant factors for any groups of Chinese tourist arrivals to Taiwan, regardless of whether the traditional or standardized-residual method is used, with the sole exception being OLS for the Group-type tourists, with decreasing CAR (with − effects). It is worth noting that there are no dynamic effects from estimating conditional volatility.

(6) Case VI: Taiwan mayors visit China

The OLS and GARCH (1,1) estimates reveal that Group-type tourists experienced a significant abnormal increase following this event. The results of the four models all showed that the numbers of Individual-type tourists increased significantly after the event. Only the OLS estimates indicated that Medical-type tourists experienced a significant abnormal increase prior to the event's occurrence. These results show that the visit by the mayors of eight counties and cities in Taiwan to Beijing, to support the cooperation and exchange event to promote "China's eight measures to benefit Taiwan", had a relatively more significant impact on Individual-type tourists. For the detailed results of the model estimation, see Tables A21–A24.

These results show that the numbers of both Group-type and Individual-type tourists increased abnormally (with + effects) after the Taiwan mayors visited China, for two and four methods of estimation, respectively. However, Medical-type tourists had a decreasing CAR (with − effects) for OLS, but not for the three time-varying conditional volatility models.

These empirical results are important as they show that CAR varies according to the type of Chinese tourists, as well as according to the method of estimation.

5.2. Empirical Results for Disaster and Accident Events

(1) Case VII: The Kaohsiung Petrochemical gas explosion

The results of the OLS, GARCH (1,1), and GJR (1,1) estimates showed that the numbers of Group-type tourists experienced a significant abnormal decrease following the occurrence of the event. The results of all four models revealed that Individual-type tourists also declined significantly. However, the results of the OLS, GARCH (1,1), and GJR (1,1) estimates showed that the numbers of Medical-type tourists significantly increased. According to the above results, the Kaohsiung Petrochemical gas explosion event had a relatively large impact on Group-type and Individual-type tourists, but it did not affect the Medical-type tourists who came to Taiwan for medical treatment. See Tables A25–A28 for the detailed results of model estimation.

These results show that the number of both Group-type and Individual-type tourists decreased abnormally (with − effects), for three and four methods of estimation, respectively. However, Medical-type tourists had an increasing CAR (with + effects) for three methods of estimation.

These empirical results are important as they show that CAR varies according to the type of Chinese tourists, as well as with the method of estimation.

(2) Case VIII: Taiwan's "gutter oil" scandal

The results of the four different kinds of models show that the numbers of Group-type and Individual-type tourists experienced significant abnormal increases following the event, but that the numbers of Medical-type tourists only increased significantly when OLS was used. As the time when the contaminated cooking oil scandal occurred in Taiwan was simultaneous to the Chinese national holidays (1 October 2014–7 October 2014), there was no impact on the willingness of Chinese tourists to visit Taiwan. On the contrary, due to the long holiday, the number of each group of Chinese visitors to Taiwan during that period was actually higher than expected, and therefore they exhibited abnormal increases. See Tables A29–A32 for the detailed results of model estimation.

These results show that the number of Group-type, Individual-type, and Medical-type tourists increased abnormally (with + effects), for four, four, and one methods of estimation, respectively. Only Medical-type tourists showed no dynamic effects from time-varying conditional volatility.

These empirical results are important as they show that CAR varies consistently and positively for all three types of Chinese tourists, as well as for the method of estimation.

(3) Case IX: TransAsia Airways Flight GE235 accident

The estimates of the four models showed that there was a significant abnormal decline in the numbers of Group-type and Individual-type tourists following the event, but only the results of OLS and GARCH (1,1) indicated that the numbers of Medical-type tourists declined significantly. From these results, it can be inferred that the crash of TransAsia Airways Flight 235 impacted the willingness of each group of Chinese tourists to visit Taiwan, due to their concerns over flight safety. The detailed results of the model estimates are given in Tables A33–A36.

These results are the polar opposite of Case VIII in that the numbers of Group-type, Individual-type, and Medical-type tourists were decreased abnormally (with − effects), for four, four, and two methods of estimation, respectively.

These empirical results are important as they show that CAR varies consistently and negatively for all three types of Chinese tourists, as well as for the method of estimation.

(4) Case X: Kaohsiung's magnitude 6.6 Meinong earthquake

While the number of Group-type tourists was not abnormally changed, the results of the OLS, GARCH (1,1) and GJR (1,1) estimates showed that the number of Individual-type tourists was significantly and abnormally reduced after the event occurred, as was the number of Medical-type tourists from the results of OLS and GJR (1,1). As the 6.6 magnitude Meinong, Kaohsiung earthquake struck at the same time as the Chinese Lunar New Year holiday (7 February 2016–13 February 2016), and the area where it happened was not a tourist attraction, Group-type tourists were not affected. However, after the Chinese New Year holiday, the numbers of Individual-type and Medical-type tourists declined significantly. See Tables A37–A40 for the detailed results of model estimation.

These results show that the number of Individual-type and Medical-type tourists decreased abnormally (with − effects), for three and one methods of estimation, respectively. Only Group-type tourists showed no significant constant or dynamic effects of time-varying conditional volatility.

These empirical results are important as they show that CAR varies consistently and negatively for two types of Chinese tourists, as well as with the method of estimation.

(5) Case XI: 95th anniversary of the founding of the Communist Party of China and the Hsiung Feng III missile mishap

The results for the four models all show that the numbers of Group-type, Individual-type, and Medical-type tourists were not affected by this accident. The Taiwan government issued a statement immediately after the mishap to point out that the incident occurred due to negligence in personnel training, and not because of political factors. It was for this reason that the willingness of each group of Chinese tourists to visit Taiwan from the mainland was not affected. See Tables A41–A44 for the detailed results of the model estimation.

As in Cases I, II, and III, the empirical results are consistent in that there are no significant factors for any group of Chinese tourist arrivals to Taiwan, regardless of the method of estimation, and whether the traditional or standardized-residual method is used.

(6) Case XII: Taiwan tour bus accident

The results for all four models showed that the numbers of Group-type, Individual-type, and Medical type tourists from China were not affected by this accident. From the empirical results, it can be seen that the tour bus accident that resulted in the deaths of tourists from Liaoning, China was due to human factors, and that the likelihood of such an incident recurring was low. In addition, the accident victims were part of a tour bus tour group, and the unfortunate event had no effect on Individual-type tourists who made their own arrangements regarding their itinerary and transportation. See Tables A45–A48 for the detailed results of the model estimation.

As in Cases I, II, III, and XI, the empirical results are consistent in that there are no significant factors for any group of Chinese tourist arrivals to Taiwan, regardless of the method of estimation, and whether the traditional or standardized-residual method is used.

6. Conclusions

The Cross-Strait relationship has long been a major focus of attention among the general public, not only in Taiwan and China, but also throughout the entire Asia–Pacific region, having become one of the more important issues of concern to the global community. The different official political stances on the two sides of the Taiwan Strait have indirectly affected private sector exchanges. Since 2008, when President Ma Ying-jeou relaxed the Cross-Strait policy, mainland Chinese have been allowed to apply to travel to Taiwan as Group-type tourists, without having to transit through a third country. With the relaxation of the conditions for Cross-Strait tourism, increasing numbers of Chinese tourists have been attracted to visit Taiwan. From 2010 onwards, Chinese tourists have accounted for the largest proportion of international tourists visiting Taiwan (though both China and Taiwan sometimes regard such tourism as domestic).

In 2016, Taiwan's 14th President Tsai Ing-wen's Cross-Strait policy was unable to satisfy the expectations for one China, which led to a gradual stalemate in Cross-Strait relations. Rumors circulated that the Chinese government had limited the number of Chinese tourists that could visit Taiwan. The data also indicated that the number of Chinese tourists visiting Taiwan was also exhibiting a clear downward trend. In addition to political factors, Taiwan's tourism environment in relation to facilities and safety considerations was also affecting the willingness of Chinese tourists to visit Taiwan.

Previous studies have rarely examined the impact of political and disaster-related events on tourism demand from China to Taiwan. In this research, an approach that has frequently been applied in financial studies, namely the event study methodology, was adopted to analyze the effects of changes in the number of three types of Chinese tourists to Taiwan caused by political events, and by disaster and accident events.

The purpose of this study was to demonstrate a potential application of the event study method to tourism data, which could be applied to analyze the impact of such detailed information on tourism. This research has used data on the numbers of Chinese tourists visiting Taiwan over the period

1 January 2014–31 October 2016 to examine the impact of Cross-Strait political events, and disaster and accident events, on the numbers of Chinese tourists visiting Taiwan during the period 2014–2016.

Major political events and increased uncertainty regarding the Cross-Strait relationship have affected the numbers of Chinese tourists visiting Taiwan. The empirical results of this paper show that President Tsai Ing-wen's lack of a specific mention of the "1992 Consensus" Cross-Strait policy resulted in an abnormal reduction in the number of Group-type Chinese tourists visiting Taiwan, an outcome that confirms the rumors that the Chinese government has limited the numbers of its citizens that can visit Taiwan.

The visit by eight of Taiwan's county and city mayors to Beijing, China, and the ensuing agreement between the two sides to jointly promote the "Eight measures to benefit Taiwan" in Taiwan and China through exchange and cooperation, resulted in the numbers of both Group-type and Individual-type tourists increasing abnormally. This paper confirms that political events have had relatively little impact on the numbers of Medical-type tourists visiting Taiwan, mainly because Medical-type tourists come to Taiwan for health checks or cosmetic treatments, and are thereby not generally affected by political events.

Given the restrictions in obtaining (daily) data from the National Immigration Agency in Taiwan, the data used in the paper focused on daily Chinese and international tourist arrivals data from 1 January 2014 to 31 October 2016.

Overall, we have focused on two major issues that affect Chinese tourists to travel to Taiwan, namely political events, and disaster and accident events. Based on the data sources, we can verify the impacts from different political events, and disaster and accident events, for three types of Chinese tourists to Taiwan, four methods of estimation, and the traditional and standardized-residual methods.

From the results of the disaster-related event research, it has been found that the impact of disasters and accidents on the number of Chinese tourists visiting Taiwan mainly depends on the level of an incident's impact. For example, the Kaohsiung Petrochemical gas explosion resulted in a significant abnormal reduction in the numbers of Group-type and Individual-type Chinese tourists visiting Taiwan.

The TransAsia Airways Flight 235 crash incident directly affected the tourists' concerns over travel safety and hence their willingness to travel, so that the numbers of each type of tourist exhibited a significant abnormal reduction. The accidental firing of a missile by the Taiwan Navy and the accident involving a Chinese tour group travelling on a tour bus did not affect the numbers of Chinese tourists visiting Taiwan.

In the cases where the events occurred on a national holiday, there was not an abnormal change in the number of Chinese tourists visiting Taiwan. If the incident took place during the Chinese New Year holiday, while it did not affect the numbers of Group-type tourists; after the holidays were over, the numbers of Individual-type and Medical-type tourists did in fact experience a significant abnormal reduction.

Based on the above empirical results, we estimated the impacts from different political events, and disaster and accident events, for three types of Chinese tourists to Taiwan. For political events, Group-type tourists are the most sensitive to the impact of Cross-Strait political events, but Individual-type and Medical-type tourists are seemingly not affected by political events.

In the past, in order to attract Chinese tourists to visit Taiwan, Taiwan businesses adopted low-cost group price competition as their business model. This not only undermined the quality of tourism in Taiwan, but also gave rise to bad money driving out good money, with the exclusion of international travelers with high spending power who would otherwise have been willing to visit Taiwan.

For disaster-related events, different levels of an incident generate different effects on the rate of change in the numbers of different types of Chinese tourists to Taiwan. These empirical results should serve as a valuable reference to the Taiwan Government, as well as to public and private policy-makers, as they formulate new economic and financial tourism policies and strategies for the future.

Therefore, in the future, tourism businesses in Taiwan should enhance their own competitiveness, and extricate themselves from the vicious cycle of price competition. The Taiwan government should also actively promote a unique style of tourism, establish tourism groups with specific purposes, and create a friendly and safe tourism environment. It should also enhance the quality of tourism in Taiwan, strengthen the depth of tourism, attract tourists with high spending power, and create new sources of tourism revenue.

Future research would also use additional data from leading tourism source countries to Taiwan, such as Hong Kong and Macao, Japan, South Korea, Singapore, Malaysia, and USA. This would enable a greater understanding of the effects of tourism demand to Taiwan caused by major events. Additionally, further research would also examine the effects of further information and factors that affect tourism demand movements.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A.

Table A1. Case I: OLS—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period $[\tau_1, \tau_2]$	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	13.66	0.54	0.53	31.44	0.84	0.82	−51.38	−0.69	−0.67
[0, 1]	24.20	0.96	0.94	20.65	0.55	0.54	30.91	0.41	0.40
[0, 2]	32.79	1.31	1.27	7.25	0.19	0.19	10.87	0.15	0.14
[0, 3]	22.26	0.89	0.85	41.95	1.13	1.08	17.94	0.24	0.23
[0, 4]	21.08	0.84	0.82	26.77	0.72	0.70	2.82	0.04	0.04
[0, 5]	−4.61	−0.18	−0.18	7.26	0.20	0.19	47.95	0.64	0.62
[0, 6]	−7.84	−0.31	−0.31	−19.91	−0.53	−0.52	−5.90	−0.08	−0.08
[0, 7]	15.89	0.63	0.62	13.55	0.36	0.36	−99.14	−1.33	−1.30
[0, 8]	31.35	1.25	1.22	−1.80	−0.05	−0.05	24.10	0.32	0.31
[0, 9]	17.39	0.69	0.68	8.08	0.22	0.21	25.03	0.34	0.33
[0, 10]	17.85	0.71	0.70	−4.17	−0.11	−0.11	−71.81	−0.96	−0.94
[0, 11]	5.54	0.22	0.22	20.30	0.55	0.53	−113.08	−1.51	−1.48
[0, 12]	−2.25	−0.09	−0.09	−23.66	−0.64	−0.62	1.11	0.01	0.01
[0, 13]	−15.50	−0.62	−0.60	−36.02	−0.97	−0.94	−0.83	−0.01	−0.01
[0, 14]	−12.78	−0.51	−0.50	−29.60	−0.80	−0.78	−42.67	−0.57	−0.56
[0, 15]	−14.42	−0.57	−0.56	6.77	0.18	0.18	10.41	0.14	0.14
[0, 16]	−43.32	−1.73	−1.67	−8.64	−0.23	−0.22	−25.34	−0.34	−0.33
[0, 17]	−6.60	−0.26	−0.26	33.69	0.90	0.88	−57.86	−0.77	−0.76
[0, 18]	−22.73	−0.91	−0.89	20.09	0.54	0.53	−9.03	−0.12	−0.12
[0, 19]	−34.47	−1.37	−1.34	−30.43	−0.82	−0.80	−103.00	−1.38	−1.34
[0, 20]	4.05	0.16	0.16	−3.21	−0.09	−0.08	−30.57	−0.41	−0.40
[0, 21]	7.00	0.28	0.27	5.70	0.15	0.15	−9.71	−0.13	−0.13
[0, 22]	19.26	0.77	0.75	10.29	0.28	0.27	2.34	0.03	0.03
[0, 23]	12.32	0.49	0.47	5.85	0.16	0.15	39.83	0.53	0.51
[0, 24]	27.48	1.10	1.07	32.14	0.86	0.84	14.09	0.19	0.18
[0, 25]	6.59	0.26	0.26	−2.22	−0.06	−0.06	−24.09	−0.32	−0.32

Table A1. *Cont.*

Event Period [τ_1, τ_2]	**Group-Type**			**Individual-Type**			**Medical-Type**		
	CAR	**t-Value**		**CAR**	**t-Value**		**CAR**	**t-Value**	
		TM	**SRM**		**TM**	**SRM**		**TM**	**SRM**
[0, 26]	−15.79	−0.63	−0.62	−12.66	−0.34	−0.33	−6.66	−0.09	−0.09
[0, 27]	−12.56	−0.50	−0.49	−10.79	−0.29	−0.28	−16.85	−0.23	−0.22
[0, 28]	−3.24	−0.13	−0.12	−29.64	−0.80	−0.77	−27.12	−0.36	−0.35
[0, 29]	−3.31	−0.13	−0.13	−36.86	−0.99	−0.97	−62.19	−0.83	−0.81
[0, 30]	−5.63	−0.22	−0.22	−3.13	−0.08	−0.08	23.12	0.31	0.30

Table A2. Case I: GARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	**Group-Type**			**Individual-Type**			**Medical-Type**		
	CAR	**t-Value**		**CAR**	**t-Value**		**CAR**	**t-Value**	
		TM	**SRM**		**TM**	**SRM**		**TM**	**SRM**
[0, 0]	13.86	0.43	0.41	32.38	0.48	0.47	−52.80	−0.63	−0.61
[0, 1]	24.51	0.75	0.73	21.25	0.32	0.31	28.30	0.34	0.33
[0, 2]	33.25	1.02	0.99	8.14	0.12	0.12	6.97	0.08	0.08
[0, 3]	22.78	0.70	0.67	42.01	0.62	0.60	12.97	0.15	0.15
[0, 4]	22.07	0.68	0.66	31.31	0.46	0.45	−4.29	−0.05	−0.05
[0, 5]	−3.54	−0.11	−0.11	11.15	0.17	0.16	39.73	0.47	0.46
[0, 6]	−6.51	−0.20	−0.20	−14.39	−0.21	−0.21	−15.70	−0.19	−0.18
[0, 7]	17.47	0.54	0.52	20.64	0.31	0.30	−110.49	−1.31	−1.28
[0, 8]	33.05	1.01	0.99	5.12	0.08	0.07	11.54	0.14	0.13
[0, 9]	19.28	0.59	0.58	15.87	0.24	0.23	11.06	0.13	0.13
[0, 10]	20.06	0.62	0.60	6.11	0.09	0.09	−87.52	−1.04	−1.02
[0, 11]	8.01	0.25	0.24	32.09	0.48	0.47	−130.34	−1.55	−1.51
[0, 12]	0.48	0.01	0.01	−10.02	−0.15	−0.15	−17.76	−0.21	−0.21
[0, 13]	−12.56	−0.39	−0.38	−21.48	−0.32	−0.31	−21.12	−0.25	−0.24
[0, 14]	−9.71	−0.30	−0.29	−15.10	−0.22	−0.22	−64.20	−0.76	−0.74
[0, 15]	−11.15	−0.34	−0.33	22.22	0.33	0.32	−12.55	−0.15	−0.15
[0, 16]	−39.71	−1.22	−1.18	9.53	0.14	0.14	−50.09	−0.59	−0.57
[0, 17]	−2.98	−0.09	−0.09	50.43	0.75	0.73	−83.56	−0.99	−0.97
[0, 18]	−18.95	−0.58	−0.57	37.12	0.55	0.54	−36.03	−0.43	−0.42
[0, 19]	−30.45	−0.93	−0.91	−11.88	−0.18	−0.17	−131.55	−1.56	−1.52
[0, 20]	8.06	0.25	0.24	13.51	0.20	0.20	−59.99	−0.71	−0.70
[0, 21]	11.15	0.34	0.33	22.56	0.34	0.33	−40.39	−0.48	−0.47
[0, 22]	23.55	0.72	0.71	27.39	0.41	0.40	−29.63	−0.35	−0.34
[0, 23]	16.50	0.51	0.48	19.92	0.30	0.28	7.24	0.09	0.08
[0, 24]	32.11	0.99	0.96	50.31	0.75	0.73	−20.58	−0.24	−0.24
[0, 25]	11.44	0.35	0.34	17.12	0.25	0.25	−60.24	−0.71	−0.70
[0, 26]	−10.77	−0.33	−0.32	7.30	0.11	0.11	−44.17	−0.52	−0.51
[0, 27]	−7.32	−0.22	−0.22	10.33	0.15	0.15	−55.83	−0.66	−0.65
[0, 28]	1.90	0.06	0.06	−11.43	−0.17	−0.16	−66.76	−0.79	−0.76
[0, 29]	2.36	0.07	0.07	−13.68	−0.20	−0.20	−104.07	−1.23	−1.21
[0, 30]	0.02	0.00	0.00	18.24	0.27	0.26	−19.63	−0.23	−0.23

Table A3. Case I: GJR(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period $[\tau_1, \tau_2]$	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	10.16	0.11	0.11	32.28	0.67	0.65	−51.27	−0.14	−0.14
[0, 1]	18.30	0.20	0.20	21.38	0.44	0.43	22.53	0.06	0.06
[0, 2]	23.95	0.27	0.26	8.34	0.17	0.17	−1.76	0.00	0.00
[0, 3]	11.44	0.13	0.12	42.56	0.88	0.84	−6.54	−0.02	−0.02
[0, 4]	3.70	0.04	0.04	30.86	0.64	0.62	2.30	0.01	0.01
[0, 5]	−24.12	−0.27	−0.26	11.01	0.23	0.22	36.81	0.10	0.10
[0, 6]	−31.46	−0.35	−0.34	−14.80	−0.31	−0.30	−12.22	−0.03	−0.03
[0, 7]	−11.76	−0.13	−0.13	19.97	0.41	0.40	−101.12	−0.28	−0.27
[0, 8]	1.15	0.01	0.01	4.64	0.10	0.09	14.76	0.04	0.04
[0, 9]	−16.25	−0.18	−0.18	15.31	0.32	0.31	15.32	0.04	0.04
[0, 10]	−20.65	−0.23	−0.23	5.06	0.10	0.10	−70.88	−0.19	−0.19
[0, 11]	−36.94	−0.41	−0.40	30.80	0.64	0.62	−108.24	−0.30	−0.29
[0, 12]	−49.03	−0.55	−0.53	−11.64	−0.24	−0.23	12.23	0.03	0.03
[0, 13]	−65.75	−0.73	−0.72	−23.19	−0.48	−0.47	10.16	0.03	0.03
[0, 14]	−65.68	−0.73	−0.72	−16.66	−0.34	−0.34	−38.18	−0.10	−0.10
[0, 15]	−70.83	−0.79	−0.77	20.56	0.42	0.41	15.06	0.04	0.04
[0, 16]	−104.78	−1.17	−1.13	7.32	0.15	0.15	−8.55	−0.02	−0.02
[0, 17]	−69.52	−0.78	−0.76	48.73	1.01	0.98	−56.89	−0.16	−0.15
[0, 18]	−88.58	−0.99	−0.97	35.49	0.73	0.72	−12.39	−0.03	−0.03
[0, 19]	−104.34	−1.17	−1.14	−13.76	−0.28	−0.28	−102.32	−0.28	−0.27
[0, 20]	−66.91	−0.75	−0.73	12.25	0.25	0.25	−48.49	−0.13	−0.13
[0, 21]	−66.78	−0.75	−0.73	21.40	0.44	0.43	−32.87	−0.09	−0.09
[0, 22]	−57.42	−0.64	−0.63	26.31	0.54	0.53	−25.48	−0.07	−0.07
[0, 23]	−64.43	−0.72	−0.69	19.75	0.41	0.39	−14.64	−0.04	−0.04
[0, 24]	−55.51	−0.62	−0.61	49.25	1.02	0.99	−18.94	−0.05	−0.05
[0, 25]	−80.10	−0.89	−0.87	15.89	0.33	0.32	−55.45	−0.15	−0.15
[0, 26]	−105.72	−1.18	−1.15	6.07	0.13	0.12	−40.01	−0.11	−0.11
[0, 27]	−106.17	−1.19	−1.16	8.94	0.18	0.18	−48.68	−0.13	−0.13
[0, 28]	−97.03	−1.08	−1.04	−11.93	−0.25	−0.24	−84.80	−0.23	−0.22
[0, 29]	−104.08	−1.16	−1.14	−15.31	−0.32	−0.31	−92.51	−0.25	−0.25
[0, 30]	−107.54	−1.20	−1.17	17.21	0.36	0.35	−25.61	−0.07	−0.07

Table A4. Case I: EGARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period $[\tau_1, \tau_2]$	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	8.92	0.08	0.08	33.31	0.82	0.80	−51.76	−0.68	−0.67
[0, 1]	15.58	0.14	0.13	19.85	0.49	0.48	32.95	0.44	0.42
[0, 2]	19.87	0.18	0.17	6.01	0.15	0.14	13.97	0.18	0.18
[0, 3]	5.78	0.05	0.05	36.27	0.90	0.86	24.56	0.32	0.31
[0, 4]	−2.51	−0.02	−0.02	35.57	0.88	0.86	1.25	0.02	0.02
[0, 5]	−31.87	−0.28	−0.28	12.27	0.30	0.30	49.51	0.65	0.64
[0, 6]	−40.31	−0.36	−0.35	−10.54	−0.26	−0.25	−6.28	−0.08	−0.08
[0, 7]	−21.73	−0.19	−0.19	27.03	0.67	0.65	−101.28	−1.34	−1.31
[0, 8]	−10.27	−0.09	−0.09	9.61	0.24	0.23	24.02	0.32	0.31
[0, 9]	−28.92	−0.26	−0.25	21.11	0.52	0.51	24.73	0.33	0.32
[0, 10]	−34.25	−0.30	−0.30	16.29	0.40	0.39	−75.95	−1.00	−0.98
[0, 11]	−51.67	−0.46	−0.45	44.65	1.11	1.08	−118.85	−1.57	−1.54
[0, 12]	−64.81	−0.58	−0.56	5.82	0.14	0.14	−7.06	−0.09	−0.09
[0, 13]	−82.77	−0.73	−0.72	−4.79	−0.12	−0.12	−9.31	−0.12	−0.12
[0, 14]	−84.13	−0.75	−0.73	0.01	0.00	0.00	−49.38	−0.65	−0.64
[0, 15]	−90.52	−0.80	−0.78	38.28	0.95	0.92	3.30	0.04	0.04
[0, 16]	−125.35	−1.11	−1.07	31.11	0.77	0.74	−36.77	−0.49	−0.47
[0, 17]	−91.79	−0.81	−0.80	66.88	1.66	1.62	−64.45	−0.85	−0.83
[0, 18]	−112.21	−1.00	−0.97	52.82	1.31	1.28	−14.55	−0.19	−0.19
[0, 19]	−129.09	−1.15	−1.12	6.24	0.15	0.15	−110.20	−1.46	−1.42
[0, 20]	−93.44	−0.83	−0.81	25.45	0.63	0.62	−32.02	−0.42	−0.41
[0, 21]	−94.70	−0.84	−0.82	33.40	0.83	0.81	−9.79	−0.13	−0.13
[0, 22]	−86.71	−0.77	−0.75	37.35	0.92	0.90	3.43	0.05	0.04
[0, 23]	−95.73	−0.85	−0.81	20.62	0.51	0.49	49.32	0.65	0.62
[0, 24]	−87.43	−0.78	−0.76	60.07	1.49	1.45	16.19	0.21	0.21
[0, 25]	−113.20	−1.00	−0.98	28.41	0.70	0.69	−22.88	−0.30	−0.30
[0, 26]	−140.12	−1.24	−1.22	18.73	0.46	0.45	−5.15	−0.07	−0.07
[0, 27]	−141.77	−1.26	−1.23	23.23	0.57	0.56	−16.19	−0.21	−0.21
[0, 28]	−134.61	−1.19	−1.15	−7.48	−0.19	−0.18	−18.34	−0.24	−0.23
[0, 29]	−142.12	−1.26	−1.23	1.58	0.04	0.04	−62.72	−0.83	−0.81
[0, 30]	−147.34	−1.31	−1.27	27.39	0.68	0.66	28.28	0.37	0.36

Table A5. Case II: OLS—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	**Group-Type**			**Individual-Type**			**Medical-Type**		
	CAR	**t-Value**		**CAR**	**t-Value**		**CAR**	**t-Value**	
		TM	**SRM**		**TM**	**SRM**		**TM**	**SRM**
[−10, −10]	9.27	0.33	0.33	13.21	0.31	0.31	55.70	0.61	0.60
[−10, −9]	−8.31	−0.30	−0.29	8.25	0.20	0.19	−1.36	−0.01	−0.01
[−10, −8]	5.94	0.21	0.21	24.61	0.58	0.56	−19.03	−0.21	−0.20
[−10, −7]	−4.03	−0.15	−0.14	23.11	0.55	0.52	49.90	0.55	0.52
[−10, −6]	−45.58	−1.64	−1.60	3.64	0.09	0.08	68.84	0.75	0.73
[−10, −5]	−13.37	−0.48	−0.47	−3.39	−0.08	−0.08	37.01	0.41	0.40
[−10, −4]	−17.77	−0.64	−0.63	−2.93	−0.07	−0.07	70.98	0.78	0.76
[−10, −3]	−6.93	−0.25	−0.25	9.78	0.23	0.23	18.99	0.21	0.20
[−10, −2]	−31.69	−1.14	−1.11	9.55	0.23	0.22	33.19	0.36	0.35
[−10, −1]	−12.91	−0.47	−0.46	4.84	0.11	0.11	0.24	0.00	0.00
[−10, 0]	7.89	0.28	0.28	11.58	0.27	0.27	96.21	1.05	1.04
[−10, 1]	−31.06	−1.12	−1.10	10.14	0.24	0.23	68.48	0.75	0.73
[−10, 2]	−32.15	−1.16	−1.13	−14.08	−0.33	−0.33	83.34	0.91	0.89
[−10, 3]	−39.89	−1.44	−1.41	−7.76	−0.18	−0.18	87.41	0.96	0.94
[−10, 4]	−6.31	−0.23	−0.22	4.91	0.12	0.11	70.98	0.78	0.76
[−10, 5]	−20.15	−0.73	−0.71	14.34	0.34	0.33	−38.17	−0.42	−0.41
[−10, 6]	−24.07	−0.87	−0.85	24.75	0.59	0.57	13.04	0.14	0.14
[−10, 7]	3.94	0.14	0.14	6.93	0.16	0.16	−23.09	−0.25	−0.25
[−10, 8]	−24.44	−0.88	−0.85	0.71	0.02	0.02	36.32	0.40	0.39
[−10, 9]	−10.19	−0.37	−0.36	−14.26	−0.34	−0.33	−49.92	−0.55	−0.53
[−10, 10]	−9.20	−0.33	−0.33	−21.61	−0.51	−0.50	−71.42	−0.78	−0.77
[−10, 11]	0.84	0.03	0.03	13.20	0.31	0.30	71.94	0.79	0.77
[−10, 12]	−15.34	−0.55	−0.54	−6.32	−0.15	−0.15	11.52	0.13	0.12
[−10, 13]	−2.99	−0.11	−0.11	13.75	0.33	0.32	97.96	1.07	1.05
[−10, 14]	4.71	0.17	0.16	4.77	0.11	0.11	31.61	0.35	0.34
[−10, 15]	−29.35	−1.06	−1.03	6.56	0.16	0.15	106.55	1.17	1.14
[−10, 16]	−1.09	−0.04	−0.04	−8.82	−0.21	−0.20	107.58	1.18	1.15
[−10, 17]	−8.37	−0.30	−0.30	−10.22	−0.24	−0.24	28.71	0.31	0.31
[−10, 18]	−1.84	−0.07	−0.07	10.77	0.26	0.25	−8.52	−0.09	−0.09
[−10, 19]	−6.10	−0.22	−0.21	−1.86	−0.04	−0.04	−31.73	−0.35	−0.34
[−10, 20]	−13.63	−0.49	−0.48	8.57	0.20	0.20	−5.68	−0.06	−0.06

Table A6. Case II: GARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period $[\tau_1, \tau_2]$	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[−10, −10]	7.18	0.10	0.09	15.05	0.23	0.22	54.85	0.57	0.56
[−10, −9]	−11.39	−0.15	−0.15	14.63	0.22	0.21	0.88	0.01	0.01
[−10, −8]	1.16	0.02	0.01	33.80	0.51	0.49	−16.22	−0.17	−0.16
[−10, −7]	−10.63	−0.14	−0.14	34.81	0.52	0.50	52.84	0.55	0.52
[−10, −6]	−56.08	−0.75	−0.73	12.68	0.19	0.19	64.35	0.67	0.65
[−10, −5]	−27.90	−0.37	−0.37	2.70	0.04	0.04	24.68	0.26	0.25
[−10, −4]	−33.95	−0.46	−0.45	6.08	0.09	0.09	59.37	0.62	0.60
[−10, −3]	−25.76	−0.35	−0.34	19.26	0.29	0.28	4.53	0.05	0.05
[−10, −2]	−51.80	−0.70	−0.68	22.85	0.34	0.33	20.77	0.22	0.21
[−10, −1]	−36.09	−0.48	−0.48	17.56	0.26	0.26	−16.56	−0.17	−0.17
[−10, 0]	−18.01	−0.24	−0.24	24.60	0.37	0.36	76.32	0.79	0.78
[−10, 1]	−58.56	−0.79	−0.77	26.20	0.39	0.39	49.50	0.51	0.50
[−10, 2]	−61.72	−0.83	−0.81	3.84	0.06	0.06	63.51	0.66	0.64
[−10, 3]	−72.27	−0.97	−0.95	10.25	0.15	0.15	64.18	0.67	0.65
[−10, 4]	−40.38	−0.54	−0.53	25.73	0.39	0.38	48.32	0.50	0.49
[−10, 5]	−57.24	−0.77	−0.75	34.69	0.52	0.51	−65.06	−0.68	−0.66
[−10, 6]	−62.82	−0.84	−0.82	48.00	0.72	0.70	−13.15	−0.14	−0.13
[−10, 7]	−37.12	−0.50	−0.49	31.45	0.47	0.46	−50.95	−0.53	−0.52
[−10, 8]	−67.31	−0.90	−0.88	27.79	0.42	0.41	8.65	0.09	0.09
[−10, 9]	−55.76	−0.75	−0.73	13.16	0.20	0.19	−80.63	−0.84	−0.82
[−10, 10]	−58.21	−0.78	−0.77	4.30	0.06	0.06	−107.88	−1.12	−1.10
[−10, 11]	−49.28	−0.66	−0.64	43.35	0.65	0.63	38.15	0.40	0.39
[−10, 12]	−67.78	−0.91	−0.89	25.12	0.38	0.37	−23.94	−0.25	−0.24
[−10, 13]	−58.35	−0.78	−0.77	44.96	0.68	0.66	58.63	0.61	0.60
[−10, 14]	−52.26	−0.70	−0.68	39.00	0.59	0.57	−6.84	−0.07	−0.07
[−10, 15]	−88.82	−1.19	−1.16	41.60	0.62	0.61	65.75	0.68	0.66
[−10, 16]	−63.36	−0.85	−0.83	26.33	0.40	0.39	63.39	0.66	0.64
[−10, 17]	−74.02	−0.99	−0.98	23.57	0.35	0.35	−21.01	−0.22	−0.21
[−10, 18]	−69.29	−0.93	−0.91	47.11	0.71	0.69	−58.05	−0.60	−0.59
[−10, 19]	−74.96	−1.01	−0.98	38.00	0.57	0.56	−79.65	−0.83	−0.81
[−10, 20]	−84.46	−1.13	−1.10	50.54	0.76	0.74	−54.07	−0.56	−0.54

Table A7. Case II: GJR(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[−10, −10]	10.33	0.30	0.29	13.35	0.31	0.30	66.30	0.23	0.23
[−10, −9]	−4.86	−0.14	−0.13	8.74	0.20	0.20	28.97	0.10	0.10
[−10, −8]	10.93	0.31	0.30	25.31	0.59	0.56	25.18	0.09	0.09
[−10, −7]	2.35	0.07	0.06	24.01	0.56	0.53	106.97	0.38	0.36
[−10, −6]	−40.33	−1.15	−1.12	4.31	0.10	0.10	121.23	0.43	0.42
[−10, −5]	−9.40	−0.27	−0.26	−2.99	−0.07	−0.07	83.80	0.30	0.29
[−10, −4]	−12.21	−0.35	−0.34	−2.31	−0.05	−0.05	132.01	0.47	0.46
[−10, −3]	−0.97	−0.03	−0.03	10.42	0.24	0.24	85.97	0.30	0.30
[−10, −2]	−23.70	−0.68	−0.66	10.50	0.24	0.24	117.45	0.41	0.40
[−10, −1]	−5.04	−0.14	−0.14	5.72	0.13	0.13	86.91	0.31	0.30
[−10, 0]	16.07	0.46	0.45	12.47	0.29	0.28	188.27	0.66	0.65
[−10, 1]	−21.22	−0.61	−0.59	11.26	0.26	0.25	175.21	0.62	0.60
[−10, 2]	−21.24	−0.61	−0.59	−12.82	−0.30	−0.29	200.69	0.71	0.69
[−10, 3]	−28.77	−0.82	−0.81	−6.50	−0.15	−0.15	209.42	0.74	0.72
[−10, 4]	6.35	0.18	0.18	6.37	0.15	0.14	206.88	0.73	0.71
[−10, 5]	−7.56	−0.22	−0.21	15.75	0.36	0.36	100.49	0.35	0.35
[−10, 6]	−9.89	−0.28	−0.28	26.38	0.61	0.59	165.88	0.59	0.57
[−10, 7]	18.91	0.54	0.53	8.65	0.20	0.19	138.43	0.49	0.48
[−10, 8]	−8.06	−0.23	−0.22	2.63	0.06	0.06	210.85	0.74	0.72
[−10, 9]	6.52	0.19	0.18	−12.33	−0.29	−0.28	130.13	0.46	0.45
[−10, 10]	6.94	0.20	0.19	−19.83	−0.46	−0.45	107.86	0.38	0.37
[−10, 11]	19.22	0.55	0.53	15.32	0.35	0.34	269.96	0.95	0.93
[−10, 12]	3.83	0.11	0.11	−4.11	−0.09	−0.09	218.24	0.77	0.75
[−10, 13]	16.24	0.46	0.45	15.92	0.37	0.36	308.27	1.09	1.06
[−10, 14]	25.58	0.73	0.71	7.17	0.17	0.16	256.52	0.90	0.88
[−10, 15]	−7.92	−0.23	−0.22	9.01	0.21	0.20	338.58	1.19	1.16
[−10, 16]	20.56	0.59	0.57	−6.37	−0.15	−0.14	344.31	1.21	1.19
[−10, 17]	12.78	0.37	0.36	−7.90	−0.18	−0.18	265.18	0.94	0.92
[−10, 18]	20.72	0.59	0.58	13.28	0.31	0.30	240.96	0.85	0.83
[−10, 19]	18.35	0.52	0.51	0.93	0.02	0.02	234.04	0.83	0.80
[−10, 20]	12.02	0.34	0.33	11.52	0.27	0.26	271.57	0.96	0.93

Table A8. Case II: EGARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[−10, −10]	8.66	0.23	0.23	12.69	0.32	0.32	61.71	0.30	0.29
[−10, −9]	−8.69	−0.23	−0.23	7.15	0.18	0.18	10.45	0.05	0.05
[−10, −8]	5.25	0.14	0.14	22.97	0.58	0.56	−1.29	−0.01	−0.01
[−10, −7]	−5.13	−0.14	−0.13	20.95	0.53	0.51	73.61	0.35	0.34
[−10, −6]	−48.66	−1.31	−1.28	1.06	0.03	0.03	98.91	0.47	0.46
[−10, −5]	−18.54	−0.50	−0.49	−6.39	−0.16	−0.16	73.45	0.35	0.35
[−10, −4]	−23.21	−0.63	−0.61	−6.47	−0.16	−0.16	113.35	0.54	0.53
[−10, −3]	−13.40	−0.36	−0.35	5.76	0.15	0.14	67.48	0.32	0.32
[−10, −2]	−38.16	−1.03	−1.00	4.97	0.13	0.12	87.54	0.42	0.41
[−10, −1]	−20.73	−0.56	−0.55	−0.20	−0.01	−0.01	60.79	0.29	0.29
[−10, 0]	−1.02	−0.03	−0.03	6.05	0.15	0.15	162.89	0.78	0.77
[−10, 1]	−40.20	−1.08	−1.06	4.06	0.10	0.10	141.08	0.68	0.66
[−10, 2]	−41.89	−1.13	−1.10	−20.67	−0.52	−0.51	161.94	0.78	0.76
[−10, 3]	−50.78	−1.37	−1.34	−14.82	−0.38	−0.37	172.16	0.83	0.81
[−10, 4]	−17.50	−0.47	−0.46	−2.70	−0.07	−0.07	161.66	0.77	0.76
[−10, 5]	−32.67	−0.88	−0.86	6.27	0.16	0.16	58.70	0.28	0.28
[−10, 6]	−36.87	−0.99	−0.97	16.14	0.41	0.40	115.84	0.56	0.54
[−10, 7]	−9.63	−0.26	−0.25	−2.19	−0.06	−0.05	85.77	0.41	0.40
[−10, 8]	−38.40	−1.03	−1.00	−8.94	−0.23	−0.22	151.14	0.72	0.70
[−10, 9]	−25.23	−0.68	−0.66	−24.40	−0.62	−0.60	71.02	0.34	0.33
[−10, 10]	−25.87	−0.70	−0.68	−32.19	−0.82	−0.80	55.79	0.27	0.26
[−10, 11]	−15.70	−0.42	−0.41	2.05	0.05	0.05	204.98	0.98	0.96
[−10, 12]	−32.66	−0.88	−0.86	−17.97	−0.46	−0.44	150.61	0.72	0.70
[−10, 13]	−21.55	−0.58	−0.57	1.62	0.04	0.04	243.22	1.17	1.14
[−10, 14]	−14.10	−0.38	−0.37	−7.90	−0.20	−0.19	182.79	0.88	0.85
[−10, 15]	−49.08	−1.32	−1.29	−6.60	−0.17	−0.16	263.82	1.26	1.23
[−10, 16]	−21.96	−0.59	−0.58	−22.46	−0.57	−0.56	270.99	1.30	1.27
[−10, 17]	−30.83	−0.83	−0.82	−24.31	−0.62	−0.61	198.39	0.95	0.94
[−10, 18]	−24.69	−0.66	−0.65	−3.85	−0.10	−0.10	167.11	0.80	0.79
[−10, 19]	−29.04	−0.78	−0.76	−17.04	−0.43	−0.42	149.78	0.72	0.70
[−10, 20]	−37.09	−1.00	−0.97	−7.12	−0.18	−0.18	181.82	0.87	0.85

Table A9. Case III: OLS—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[−10, −10]	5.16	0.19	0.19	2.09	0.05	0.05	160.17	1.79	1.75
[−10, −9]	−30.70	−1.14	−1.12	8.41	0.20	0.20	190.49	2.13	2.09
[−10, −8]	−28.43	−1.06	−1.04	16.27	0.39	0.38	78.31	0.87	0.86
[−10, −7]	−40.46	−1.51	−1.47	6.80	0.16	0.16	61.67	0.69	0.67
[−10, −6]	−61.14	−2.28	−2.24	6.58	0.16	0.16	102.99	1.15	1.13
[−10, −5]	−35.51	−1.32	−1.30	1.40	0.03	0.03	53.78	0.60	0.59
[−10, −4]	−27.64	−1.03	−1.01	4.72	0.11	0.11	77.14	0.86	0.85
[−10, −3]	−25.18	−0.94	−0.91	−10.21	−0.25	−0.24	92.73	1.04	1.01
[−10, −2]	−53.66	−2.00	−1.95	9.42	0.23	0.22	69.13	0.77	0.75
[−10, −1]	−45.53	−1.70	−1.65	31.06	0.75	0.73	26.10	0.29	0.28
[−10, 0]	−35.49	−1.32	−1.29	26.53	0.64	0.62	63.90	0.71	0.70
[−10, 1]	−46.41	−1.73	−1.69	−10.25	−0.25	−0.24	94.44	1.05	1.03
[−10, 2]	−40.34	−1.50	−1.47	3.59	0.09	0.08	186.93	2.09	2.04
[−10, 3]	−36.82	−1.37	−1.35	2.18	0.05	0.05	128.85	1.44	1.41
[−10, 4]	−12.10	−0.45	−0.44	17.94	0.43	0.42	138.84	1.55	1.52
[−10, 5]	−45.64	−1.70	−1.65	−7.53	−0.18	−0.18	106.35	1.19	1.15
[−10, 6]	−42.65	−1.59	−1.55	15.72	0.38	0.37	128.75	1.44	1.40
[−10, 7]	−26.97	−1.01	−0.98	28.67	0.69	0.67	69.94	0.78	0.76
[−10, 8]	−23.51	−0.88	−0.85	13.84	0.33	0.32	144.21	1.61	1.57
[−10, 9]	−26.28	−0.98	−0.96	4.25	0.10	0.10	131.81	1.47	1.44
[−10, 10]	−27.82	−1.04	−1.01	7.61	0.18	0.18	135.79	1.52	1.48
[−10, 11]	−0.64	−0.02	−0.02	22.39	0.54	0.52	141.20	1.58	1.54
[−10, 12]	−50.16	−1.87	−1.81	−4.61	−0.11	−0.11	80.84	0.90	0.87
[−10, 13]	−53.98	−2.01	−1.93	0.73	0.02	0.02	79.65	0.89	0.85
[−10, 14]	−43.62	−1.63	−1.55	0.96	0.02	0.02	89.81	1.00	0.96
[−10, 15]	−44.63	−1.66	−1.62	6.23	0.15	0.15	149.34	1.67	1.62
[−10, 16]	−12.59	−0.47	−0.46	18.62	0.45	0.44	78.99	0.88	0.86
[−10, 17]	−24.56	−0.92	−0.90	8.40	0.20	0.20	124.89	1.39	1.37
[−10, 18]	−11.21	−0.42	−0.41	2.78	0.07	0.07	78.18	0.87	0.85
[−10, 19]	−39.86	−1.49	−1.44	2.22	0.05	0.05	90.85	1.01	0.99
[−10, 20]	−43.98	−1.64	−1.58	4.30	0.10	0.10	143.90	1.61	1.55

Table A10. Case III: GARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	**Group-Type**			**Individual-Type**			**Medical-Type**		
	CAR	**t-Value**		**CAR**	**t-Value**		**CAR**	**t-Value**	
		TM	**SRM**		**TM**	**SRM**		**TM**	**SRM**
[−10, −10]	5.33	0.10	0.10	2.16	0.05	0.05	149.85	0.48	0.47
[−10 ,−9]	−32.51	−0.63	−0.62	8.28	0.20	0.20	170.02	0.55	0.54
[−10, −8]	−30.78	−0.60	−0.58	16.13	0.39	0.38	47.57	0.15	0.15
[−10, −7]	−43.16	−0.84	−0.82	6.66	0.16	0.16	20.65	0.07	0.06
[−10, −6]	−66.74	−1.29	−1.27	6.13	0.15	0.15	51.91	0.17	0.16
[−10, −5]	−42.96	−0.83	−0.82	0.78	0.02	0.02	−7.45	−0.02	−0.02
[−10, −4]	−36.58	−0.71	−0.70	3.96	0.10	0.09	5.73	0.02	0.02
[−10, −3]	−32.74	−0.63	−0.62	−10.75	−0.26	−0.25	10.88	0.04	0.03
[−10, −2]	−63.10	−1.22	−1.19	8.69	0.21	0.21	−22.87	−0.07	−0.07
[−10, −1]	−55.94	−1.08	−1.05	30.26	0.73	0.71	−76.13	−0.25	−0.24
[−10, 0]	−48.00	−0.93	−0.91	25.52	0.62	0.60	−48.45	−0.16	−0.15
[−10, 1]	−59.88	−1.16	−1.13	−11.33	−0.27	−0.27	−28.15	−0.09	−0.09
[−10, 2]	−55.45	−1.08	−1.05	2.36	0.06	0.06	54.18	0.17	0.17
[−10, 3]	−53.77	−1.04	−1.02	0.78	0.02	0.02	−14.06	−0.05	−0.04
[−10, 4]	−30.76	−0.60	−0.59	16.37	0.40	0.39	−14.23	−0.05	−0.05
[−10, 5]	−63.64	−1.23	−1.20	−8.97	−0.22	−0.21	−57.09	−0.18	−0.18
[−10, 6]	−62.77	−1.22	−1.19	14.07	0.34	0.33	−44.82	−0.14	−0.14
[−10, 7]	−48.16	−0.93	−0.91	26.93	0.65	0.64	−113.85	−0.37	−0.36
[−10, 8]	−45.88	−0.89	−0.87	12.01	0.29	0.28	−49.79	−0.16	−0.16
[−10, 9]	−51.23	−0.99	−0.97	2.15	0.05	0.05	−72.27	−0.23	−0.23
[−10, 10]	−53.40	−1.04	−1.01	5.48	0.13	0.13	−78.55	−0.25	−0.25
[−10, 11]	−27.11	−0.53	−0.51	20.20	0.49	0.48	−83.38	−0.27	−0.26
[−10, 12]	−77.08	−1.49	−1.45	−6.80	−0.16	−0.16	−154.02	−0.50	−0.48
[−10, 13]	−81.48	−1.58	−1.52	−1.49	−0.04	−0.03	−165.47	−0.53	−0.51
[−10, 14]	−71.64	−1.39	−1.32	−1.27	−0.03	−0.03	−165.58	−0.53	−0.51
[−10, 15]	−76.29	−1.48	−1.44	3.60	0.09	0.08	−116.05	−0.37	−0.36
[−10, 16]	−46.62	−0.90	−0.89	15.75	0.38	0.37	−196.50	−0.63	−0.62
[−10, 17]	−59.84	−1.16	−1.14	5.43	0.13	0.13	−160.80	−0.52	−0.51
[−10, 18]	−47.05	−0.91	−0.89	−0.22	−0.01	−0.01	−217.78	−0.70	−0.69
[−10, 19]	−76.59	−1.48	−1.44	−0.84	−0.02	−0.02	−215.34	−0.70	−0.68
[−10, 20]	−81.07	−1.57	−1.51	1.25	0.03	0.03	−172.57	−0.56	−0.54

Table A11. Case III: GJR(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[−10, −10]	7.11	0.24	0.23	−0.34	−0.01	−0.01	157.94	1.49	1.46
[−10, −9]	−28.60	−0.96	−0.95	4.67	0.08	0.08	186.43	1.75	1.72
[−10, −8]	−24.97	−0.84	−0.82	10.46	0.17	0.17	72.15	0.68	0.67
[−10, −7]	−35.49	−1.19	−1.16	−1.17	−0.02	−0.02	53.38	0.50	0.49
[−10, −6]	−56.78	−1.91	−1.88	−2.23	−0.04	−0.04	93.04	0.88	0.86
[−10, −5]	−30.89	−1.04	−1.02	−8.79	−0.15	−0.14	41.98	0.39	0.39
[−10, −4]	−22.45	−0.76	−0.74	−7.04	−0.12	−0.11	63.42	0.60	0.59
[−10, −3]	−17.04	−0.57	−0.56	−25.03	−0.42	−0.40	76.55	0.72	0.70
[−10, −2]	−45.28	−1.52	−1.49	−6.77	−0.11	−0.11	51.10	0.48	0.47
[−10, −1]	−36.15	−1.22	−1.18	13.03	0.22	0.21	6.05	0.06	0.06
[−10, 0]	−26.06	−0.88	−0.86	7.25	0.12	0.12	42.05	0.40	0.39
[−10, 1]	−35.97	−1.21	−1.18	−31.37	−0.52	−0.51	70.57	0.66	0.65
[−10, 2]	−29.46	−0.99	−0.97	−19.02	−0.32	−0.31	161.17	1.52	1.48
[−10, 3]	−25.67	−0.86	−0.85	−21.82	−0.36	−0.35	101.23	0.95	0.93
[−10, 4]	−0.57	−0.02	−0.02	−7.51	−0.12	−0.12	109.35	1.03	1.01
[−10, 5]	−31.75	−1.07	−1.04	−35.67	−0.59	−0.57	74.53	0.70	0.68
[−10, 6]	−28.73	−0.97	−0.94	−13.65	−0.23	−0.22	95.13	0.90	0.87
[−10, 7]	−12.13	−0.41	−0.40	−2.50	−0.04	−0.04	34.32	0.32	0.31
[−10, 8]	−7.85	−0.26	−0.26	−19.06	−0.32	−0.31	106.61	1.00	0.98
[−10, 9]	−10.96	−0.37	−0.36	−29.65	−0.49	−0.48	92.50	0.87	0.85
[−10, 10]	−11.22	−0.38	−0.37	−28.31	−0.47	−0.46	94.40	0.89	0.87
[−10, 11]	17.03	0.57	0.56	−15.41	−0.26	−0.25	97.77	0.92	0.90
[−10, 12]	−31.07	−1.05	−1.01	−44.51	−0.74	−0.71	35.29	0.33	0.32
[−10, 13]	−33.57	−1.13	−1.09	−41.21	−0.68	−0.66	32.02	0.30	0.29
[−10, 14]	−21.83	−0.73	−0.70	−43.06	−0.71	−0.68	40.07	0.38	0.36
[−10, 15]	−24.07	−0.81	−0.79	−38.25	−0.63	−0.62	98.08	0.92	0.90
[−10, 16]	7.80	0.26	0.26	−26.96	−0.45	−0.44	25.99	0.24	0.24
[−10, 17]	−3.40	−0.11	−0.11	−38.87	−0.65	−0.63	69.92	0.66	0.64
[−10, 18]	11.29	0.38	0.37	−46.55	−0.77	−0.75	21.11	0.20	0.19
[−10, 19]	−16.30	−0.55	−0.53	−48.99	−0.81	−0.79	31.75	0.30	0.29
[−10, 20]	−18.91	−0.64	−0.61	−49.06	−0.81	−0.78	82.67	0.78	0.75

Table A12. Case III: EGARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[−10, −10]	8.83	0.28	0.28	0.79	0.02	0.02	160.50	1.50	1.47
[−10, −9]	−29.20	−0.94	−0.92	5.95	0.12	0.11	193.68	1.81	1.78
[−10, −8]	−25.17	−0.81	−0.79	12.55	0.25	0.24	82.66	0.77	0.76
[−10, −7]	−34.93	−1.12	−1.10	1.81	0.04	0.03	66.96	0.63	0.61
[−10, −6]	−60.25	−1.94	−1.90	0.49	0.01	0.01	112.23	1.05	1.03
[−10, −5]	−36.43	−1.17	−1.15	−5.85	−0.11	−0.11	65.74	0.61	0.60
[−10, −4]	−29.38	−0.95	−0.93	−3.73	−0.07	−0.07	91.39	0.85	0.84
[−10, −3]	−19.98	−0.64	−0.62	−20.04	−0.39	−0.38	105.87	0.99	0.96
[−10, −2]	−50.35	−1.62	−1.58	−1.58	−0.03	−0.03	85.02	0.80	0.78
[−10, −1]	−41.63	−1.34	−1.30	18.83	0.37	0.36	43.66	0.41	0.40
[−10, 0]	−34.07	−1.10	−1.07	13.15	0.26	0.25	84.48	0.79	0.77
[−10, 1]	−44.36	−1.43	−1.39	−24.85	−0.49	−0.47	116.67	1.09	1.06
[−10, 2]	−39.54	−1.27	−1.24	−12.20	−0.24	−0.23	211.63	1.98	1.93
[−10, 3]	−37.78	−1.22	−1.19	−14.77	−0.29	−0.28	156.24	1.46	1.43
[−10, 4]	−14.50	−0.47	−0.46	−0.19	0.00	0.00	168.79	1.58	1.55
[−10, 5]	−43.05	−1.39	−1.34	−27.00	−0.53	−0.51	136.05	1.27	1.23
[−10, 6]	−42.59	−1.37	−1.34	−4.90	−0.10	−0.09	161.48	1.51	1.47
[−10, 7]	−26.58	−0.86	−0.83	6.83	0.13	0.13	104.45	0.98	0.95
[−10, 8]	−23.11	−0.74	−0.72	−9.21	−0.18	−0.18	180.65	1.69	1.64
[−10, 9]	−29.67	−0.96	−0.94	−19.92	−0.39	−0.38	171.83	1.61	1.57
[−10, 10]	−29.69	−0.96	−0.93	−17.81	−0.35	−0.34	177.08	1.66	1.62
[−10, 11]	−1.70	−0.05	−0.05	−4.26	−0.08	−0.08	184.05	1.72	1.68
[−10, 12]	−49.26	−1.59	−1.53	−32.52	−0.64	−0.61	124.76	1.17	1.13
[−10, 13]	−51.44	−1.66	−1.59	−28.44	−0.56	−0.53	124.78	1.17	1.12
[−10, 14]	−39.25	−1.26	−1.20	−29.47	−0.58	−0.55	136.07	1.27	1.21
[−10, 15]	−46.92	−1.51	−1.47	−25.25	−0.49	−0.48	200.43	1.87	1.82
[−10, 16]	−18.11	−0.58	−0.57	−13.99	−0.27	−0.27	133.43	1.25	1.22
[−10, 17]	−30.24	−0.97	−0.95	−25.41	−0.50	−0.49	181.33	1.70	1.66
[−10, 18]	−15.20	−0.49	−0.48	−32.29	−0.63	−0.61	135.80	1.27	1.24
[−10, 19]	−43.04	−1.39	−1.35	−34.09	−0.67	−0.65	150.05	1.40	1.36
[−10, 20]	−44.94	−1.45	−1.39	−33.27	−0.65	−0.63	204.05	1.91	1.84

Table A13. Case IV: OLS—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[−10, −10]	34.16	1.54	1.52	34.15	0.91	0.90	54.99	0.78	0.77
[−10 ,−9]	−10.42	−0.47	−0.46	18.30	0.49	0.48	57.01	0.81	0.80
[−10, −8]	3.44	0.16	0.15	25.86	0.69	0.68	83.84	1.19	1.17
[−10, −7]	−17.28	−0.78	−0.77	5.60	0.15	0.15	85.41	1.21	1.19
[−10, −6]	−1.56	−0.07	−0.07	25.75	0.69	0.67	48.79	0.69	0.68
[−10, −5]	0.02	0.00	0.00	14.94	0.40	0.39	0.91	0.01	0.01
[−10, −4]	25.15	1.14	1.12	29.92	0.80	0.78	−130.89	−1.85	−1.82
[−10, −3]	47.40	2.14	2.11	49.47	1.32	1.30	−28.62	−0.41	−0.40
[−10, −2]	−12.05	−0.54	−0.53	40.07	1.07	1.05	−60.18	−0.85	−0.84
[−10, −1]	24.56	1.11	1.09	43.11	1.15	1.13	−24.37	−0.35	−0.34
[−10, 0]	46.52	2.10	2.07	83.99	2.24	2.20	−17.14	−0.24	−0.24
[−10, 1]	81.60	3.69 *	3.63 *	56.07	1.49	1.47	31.27	0.44	0.44
[−10, 2]	99.79	4.51 **	4.44 **	62.56	1.67	1.64	−42.54	−0.60	−0.59
[−10, 3]	106.06	4.79 **	4.71 **	70.71	1.88	1.85	−17.11	−0.24	−0.24
[−10, 4]	125.32	5.66 **	5.58 **	107.40	2.86	2.82	102.25	1.45	1.43
[−10, 5]	91.15	4.12 *	4.05 *	101.34	2.70	2.65	70.06	0.99	0.98
[−10, 6]	82.22	3.72 *	3.66 *	120.37	3.21 *	3.16 *	−90.69	−1.28	−1.27
[−10, 7]	106.70	4.82 **	4.75 **	141.77	3.78 *	3.72 *	17.59	0.25	0.25
[−10, 8]	107.43	4.86 **	4.78 **	138.98	3.70 *	3.65 *	−64.56	−0.91	−0.90
[−10, 9]	118.65	5.36 **	5.28 **	137.37	3.66 *	3.60 *	26.75	0.38	0.37
[−10, 10]	127.78	5.78 **	5.68 **	132.07	3.52 *	3.46 *	−106.14	−1.50	−1.48
[−10, 11]	145.84	6.59 **	6.49 **	123.24	3.28 *	3.23 *	−71.55	−1.01	−1.00
[−10, 12]	101.45	4.59 **	4.51 **	116.94	3.12 *	3.06 *	−8.19	−0.12	−0.11
[−10, 13]	107.00	4.84 **	4.76 **	115.69	3.08 *	3.03 *	−8.08	−0.11	−0.11
[−10, 14]	124.09	5.61 **	5.52 **	144.69	3.85 *	3.79 *	−16.41	−0.23	−0.23
[−10, 15]	94.22	4.26 *	4.19 *	127.17	3.39 *	3.34 *	−55.82	−0.79	−0.78
[−10, 16]	88.80	4.01 *	3.95 *	114.97	3.06 *	3.02 *	−27.97	−0.40	−0.39
[−10, 17]	100.93	4.56 **	4.44 **	145.31	3.87 *	3.76 *	5.77	0.08	0.08
[−10, 18]	123.14	5.56 **	5.48 *	170.81	4.55 **	4.48 **	90.92	1.29	1.27
[−10, 19]	110.07	4.97 **	4.89 *	169.21	4.51 **	4.44 **	58.15	0.82	0.81
[−10, 20]	82.15	3.71 *	3.65 *	169.72	4.52 **	4.45 **	17.53	0.25	0.24

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A14. Case IV: GARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[−10, −10]	31.30	1.21	1.19	32.32	1.09	1.08	54.44	0.76	0.75
[−10, −9]	−9.14	−0.35	−0.35	17.20	0.58	0.57	57.47	0.80	0.79
[−10, −8]	9.99	0.39	0.38	25.89	0.88	0.86	85.57	1.20	1.18
[−10, −7]	−1.56	−0.06	−0.06	8.20	0.28	0.27	89.26	1.25	1.23
[−10, −6]	1.68	0.06	0.06	23.00	0.78	0.76	49.95	0.70	0.68
[−10, −5]	−0.57	−0.02	−0.02	10.01	0.34	0.33	1.30	0.02	0.02
[−10, −4]	17.97	0.69	0.68	21.79	0.74	0.72	−131.88	−1.84	−1.81
[−10, −3]	37.93	1.47	1.44	39.72	1.34	1.32	−30.03	−0.42	−0.41
[−10, −2]	−11.83	−0.46	−0.45	33.06	1.12	1.10	−59.34	−0.83	−0.82
[−10, −1]	20.21	0.78	0.77	33.66	1.14	1.12	−24.46	−0.34	−0.34
[−10, 0]	46.18	1.78	1.76	75.21	2.54	2.51	−16.25	−0.23	−0.22
[−10, 1]	84.72	3.27 *	3.22 *	47.78	1.62	1.59	33.02	0.46	0.45
[−10, 2]	101.58	3.93 *	3.87 *	52.99	1.79	1.77	−41.01	−0.57	−0.56
[−10, 3]	101.68	3.93 *	3.86 *	58.09	1.97	1.93	−16.87	−0.24	−0.23
[−10, 4]	122.97	4.75 **	4.68 **	94.75	3.21 *	3.16 *	103.04	1.44	1.42
[−10, 5]	96.84	3.74 *	3.68 *	90.84	3.07 *	3.02 *	72.72	1.02	1.00
[−10, 6]	85.91	3.32 *	3.27 *	108.34	3.67 *	3.61 *	−88.38	−1.24	−1.22
[−10, 7]	107.62	4.16 *	4.09 *	127.94	4.33 *	4.26 *	19.37	0.27	0.27
[−10, 8]	108.40	4.19 *	4.12 *	124.39	4.21 *	4.14 *	−62.69	−0.88	−0.86
[−10, 9]	120.44	4.65 **	4.58 **	122.30	4.14 *	4.07 *	28.90	0.40	0.40
[−10, 10]	124.09	4.79 **	4.72 **	114.20	3.86 *	3.80 *	−105.13	−1.47	−1.45
[−10, 11]	139.54	5.39 **	5.31 **	103.63	3.51 *	3.45 *	−71.03	−0.99	−0.98
[−10, 12]	103.87	4.01 *	3.94 *	99.73	3.37 *	3.32 *	−5.64	−0.08	−0.08
[−10, 13]	104.47	4.04 *	3.97 *	95.89	3.24 *	3.19 *	−6.55	−0.09	−0.09
[−10, 14]	117.73	4.55 **	4.48 **	122.69	4.15 *	4.09 *	−15.64	−0.22	−0.22
[−10, 15]	85.30	3.30 *	3.25 *	103.46	3.50 *	3.45 *	−55.53	−0.78	−0.76
[−10, 16]	82.36	3.18 *	3.13 *	91.37	3.09 *	3.04 *	−27.05	−0.38	−0.37
[−10, 17]	74.54	2.88	2.80	113.63	3.84 *	3.74 *	2.33	0.03	0.03
[−10, 18]	94.14	3.64 *	3.58 *	137.40	4.65 **	4.58 **	86.99	1.22	1.20
[−10, 19]	87.01	3.36 *	3.31 *	137.18	4.64 **	4.57 **	55.63	0.78	0.77
[−10, 20]	65.04	2.51	2.47	139.08	4.71 **	4.63 **	16.43	0.23	0.23

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A15. Case IV: GJR(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	**Group-Type**			**Individual-Type**			**Medical-Type**		
	CAR	**t-Value**		**CAR**	**t-Value**		**CAR**	**t-Value**	
		TM	**SRM**		**TM**	**SRM**		**TM**	**SRM**
[−10, −10]	31.65	1.02	1.01	29.23	0.43	0.42	61.21	0.28	0.27
[−10, −9]	−8.44	−0.27	−0.27	12.57	0.18	0.18	71.19	0.32	0.32
[−10, −8]	11.02	0.36	0.35	19.97	0.29	0.29	106.27	0.48	0.47
[−10, −7]	−0.19	−0.01	−0.01	1.85	0.03	0.03	117.05	0.53	0.52
[−10, −6]	3.42	0.11	0.11	11.44	0.17	0.16	84.26	0.38	0.37
[−10, −5]	1.52	0.05	0.05	−4.86	−0.07	−0.07	42.35	0.19	0.19
[−10, −4]	20.42	0.66	0.65	3.01	0.04	0.04	−84.15	−0.38	−0.37
[−10, −3]	40.73	1.32	1.30	17.98	0.26	0.26	24.48	0.11	0.11
[−10, −2]	−8.70	−0.28	−0.28	11.01	0.16	0.16	2.27	0.01	0.01
[−10, −1]	23.70	0.77	0.76	8.14	0.12	0.12	43.87	0.20	0.19
[−10, 0]	50.01	1.62	1.59	48.12	0.71	0.69	59.03	0.27	0.26
[−10, 1]	88.90	2.88	2.83	18.99	0.28	0.27	115.24	0.52	0.51
[−10, 2]	106.11	3.44 *	3.38 *	21.45	0.31	0.31	48.02	0.22	0.21
[−10, 3]	106.56	3.45 *	3.39 *	22.74	0.33	0.33	78.85	0.36	0.35
[−10, 4]	128.20	4.15 *	4.09 *	57.38	0.84	0.83	205.65	0.93	0.91
[−10, 5]	102.41	3.32 *	3.26 *	52.80	0.77	0.76	182.39	0.82	0.81
[−10, 6]	91.83	2.97 *	2.93 *	67.40	0.99	0.97	28.08	0.13	0.12
[−10, 7]	113.89	3.69 *	3.63 *	83.94	1.23	1.21	142.60	0.64	0.63
[−10, 8]	115.02	3.72 *	3.67 *	77.93	1.14	1.13	67.39	0.30	0.30
[−10, 9]	127.40	4.12 *	4.06 *	73.57	1.08	1.06	165.84	0.75	0.74
[−10, 10]	131.41	4.25 *	4.18 *	61.80	0.91	0.89	38.51	0.17	0.17
[−10, 11]	147.21	4.77 **	4.69 **	48.20	0.71	0.70	79.39	0.36	0.35
[−10, 12]	111.88	3.62 *	3.56 *	43.78	0.64	0.63	151.85	0.68	0.67
[−10, 13]	112.83	3.65 *	3.59 *	36.39	0.53	0.53	157.66	0.71	0.70
[−10, 14]	126.44	4.09 *	4.03 *	59.88	0.88	0.86	155.31	0.70	0.69
[−10, 15]	94.37	3.06 *	3.01 *	37.63	0.55	0.54	122.20	0.55	0.54
[−10, 16]	91.78	2.97 *	2.93 *	23.63	0.35	0.34	157.60	0.71	0.70
[−10, 17]	84.33	2.73	2.66	39.03	0.57	0.56	193.29	0.87	0.85
[−10, 18]	104.28	3.38 *	3.32 *	59.76	0.88	0.86	284.73	1.28	1.26
[−10, 19]	97.49	3.16 *	3.11 *	58.40	0.86	0.84	260.37	1.17	1.15
[−10, 20]	75.86	2.46	2.42	59.15	0.87	0.85	228.17	1.03	1.01

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A16. Case IV: EGARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period $[\tau_1, \tau_2]$	**Group-Type**			**Individual-Type**			**Medical-Type**		
	CAR	**t-Value**		**CAR**	**t-Value**		**CAR**	**t-Value**	
		TM	**SRM**		**TM**	**SRM**		**TM**	**SRM**
[−10, −10]	32.49	0.84	0.82	29.71	0.46	0.46	66.87	0.18	0.17
[−10, −9]	−7.68	−0.20	−0.19	12.84	0.20	0.20	82.37	0.22	0.21
[−10, −8]	11.57	0.30	0.29	19.93	0.31	0.31	122.95	0.32	0.32
[−10, −7]	−0.38	−0.01	−0.01	1.11	0.02	0.02	139.15	0.37	0.36
[−10, −6]	5.33	0.14	0.13	12.11	0.19	0.18	112.21	0.30	0.29
[−10, −5]	4.40	0.11	0.11	−3.61	−0.06	−0.06	75.99	0.20	0.20
[−10, −4]	24.63	0.63	0.62	5.10	0.08	0.08	−44.78	−0.12	−0.12
[−10, −3]	45.71	1.18	1.16	20.49	0.32	0.31	69.50	0.18	0.18
[−10, −2]	−4.52	−0.12	−0.11	12.77	0.20	0.20	52.70	0.14	0.14
[−10, −1]	28.94	0.75	0.73	10.54	0.16	0.16	100.00	0.26	0.26
[−10, 0]	55.19	1.42	1.40	50.33	0.78	0.77	120.68	0.32	0.31
[−10, 1]	94.09	2.42	2.39	21.06	0.33	0.32	182.42	0.48	0.47
[−10, 2]	111.95	2.88	2.84	23.85	0.37	0.37	120.84	0.32	0.31
[−10, 3]	113.67	2.93 *	2.88	25.94	0.40	0.40	157.39	0.41	0.41
[−10, 4]	135.52	3.49 *	3.44 *	60.58	0.94	0.93	289.75	0.76	0.75
[−10, 5]	109.14	2.81	2.76	55.41	0.86	0.85	271.93	0.72	0.70
[−10, 6]	99.28	2.56	2.52	70.41	1.10	1.08	123.27	0.32	0.32
[−10, 7]	122.17	3.15 *	3.10 *	87.41	1.36	1.34	243.45	0.64	0.63
[−10, 8]	123.77	3.19 *	3.14 *	81.60	1.27	1.25	173.84	0.46	0.45
[−10, 9]	136.51	3.52 *	3.46 *	77.35	1.20	1.19	277.88	0.73	0.72
[−10, 10]	141.70	3.65 *	3.59 *	66.33	1.03	1.02	156.27	0.41	0.41
[−10, 11]	158.32	4.08 *	4.01 *	53.18	0.83	0.82	202.81	0.53	0.53
[−10, 12]	122.30	3.15 *	3.10 *	48.10	0.75	0.74	280.69	0.74	0.73
[−10, 13]	124.38	3.20 *	3.15 *	41.39	0.64	0.63	292.21	0.77	0.76
[−10, 14]	138.96	3.58 *	3.52 *	65.46	1.02	1.00	295.54	0.78	0.77
[−10, 15]	107.68	2.77	2.73	43.65	0.68	0.67	268.08	0.71	0.70
[−10, 16]	105.23	2.71	2.67	29.61	0.46	0.45	309.03	0.81	0.80
[−10, 17]	100.86	2.60	2.53	47.15	0.73	0.71	350.74	0.92	0.90
[−10, 18]	121.62	3.13 *	3.08 *	68.33	1.06	1.05	447.83	1.18	1.16
[−10, 19]	114.52	2.95 *	2.90 *	66.59	1.04	1.02	428.95	1.13	1.11
[−10, 20]	92.58	2.38	2.35	66.97	1.04	1.03	402.24	1.06	1.04

Note: * denotes significance at the 10% level.

Table A17. Case V: OLS—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[−10, −10]	−32.96	−1.36	−1.33	−12.93	−0.32	−0.31	61.37	0.62	0.61
[−10, −9]	−28.58	−1.18	−1.13	−19.31	−0.47	−0.46	103.52	1.04	1.01
[−10, −8]	−34.42	−1.42	−1.39	−34.99	−0.86	−0.84	82.38	0.83	0.82
[−10, −7]	−25.58	−1.05	−1.03	−21.17	−0.52	−0.51	129.40	1.31	1.28
[−10, −6]	−49.76	−2.05	−2.00	−18.73	−0.46	−0.45	61.36	0.62	0.60
[−10, −5]	−47.51	−1.96	−1.93	−27.98	−0.68	−0.67	53.56	0.54	0.53
[−10, −4]	−37.33	−1.54	−1.51	−49.55	−1.21	−1.19	78.26	0.79	0.78
[−10, −3]	−41.53	−1.71	−1.68	−31.87	−0.78	−0.77	85.57	0.86	0.85
[−10, −2]	−30.93	−1.27	−1.25	−34.90	−0.85	−0.84	159.54	1.61	1.58
[−10, −1]	−38.94	−1.60	−1.55	−46.41	−1.14	−1.10	−106.69	−1.08	−1.04
[−10, 0]	−39.42	−1.62	−1.58	−29.24	−0.72	−0.70	−105.01	−1.06	−1.03
[−10, 1]	−36.34	−1.50	−1.47	−20.13	−0.49	−0.48	−17.77	−0.18	−0.18
[−10, 2]	−43.42	−1.79	−1.76	−39.64	−0.97	−0.96	170.96	1.72	1.70
[−10, 3]	−46.19	−1.90	−1.87	−56.16	−1.38	−1.35	29.96	0.30	0.30
[−10, 4]	−32.28	−1.33	−1.30	−34.72	−0.85	−0.83	77.10	0.78	0.76
[−10, 5]	−16.99	−0.70	−0.68	−32.96	−0.81	−0.79	66.08	0.67	0.65
[−10, 6]	−36.57	−1.50	−1.48	−55.84	−1.37	−1.35	3.99	0.04	0.04
[−10, 7]	−40.35	−1.66	−1.63	−44.23	−1.08	−1.07	16.75	0.17	0.17
[−10, 8]	−51.49	−2.12	−2.09	−35.77	−0.88	−0.86	23.60	0.24	0.23
[−10, 9]	−67.44	−2.78	−2.73	−43.04	−1.05	−1.04	220.30	2.22	2.19
[−10, 10]	−68.55	−2.82	−2.78	−43.96	−1.08	−1.06	105.48	1.06	1.05
[−10, 11]	−76.15	−3.13 *	−3.08 *	−50.54	−1.24	−1.22	120.17	1.21	1.19
[−10, 12]	−81.02	−3.33 *	−3.28 *	−39.36	−0.96	−0.95	4.94	0.05	0.05
[−10, 13]	−84.93	−3.49 *	−3.43 *	−32.21	−0.79	−0.77	−113.75	−1.15	−1.13
[−10, 14]	−57.46	−2.36	−2.26	10.51	0.26	0.25	3.50	0.04	0.03
[−10, 15]	−85.57	−3.52 *	−3.42 *	52.75	1.29	1.25	−3.43	−0.03	−0.03
[−10, 16]	−83.87	−3.45 *	−3.37 *	1.17	0.03	0.03	−36.17	−0.36	−0.36
[−10, 17]	−84.93	−3.49 *	−3.42 *	−42.91	−1.05	−1.03	87.49	0.88	0.86
[−10, 18]	−86.15	−3.55 *	−3.49 *	−24.12	−0.59	−0.58	26.67	0.27	0.26
[−10, 19]	−63.30	−2.60	−2.56	−0.24	−0.01	−0.01	−84.63	−0.85	−0.84
[−10, 20]	−58.10	−2.39	−2.34	−8.00	−0.20	−0.19	−56.51	−0.57	−0.56

Note: * denotes significance at the 10% level.

Table A18. Case V: GARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[−10, −10]	−32.40	−1.07	−1.05	−14.71	−0.29	−0.29	62.53	0.57	0.55
[−10, −9]	−26.94	−0.89	−0.86	−20.83	−0.42	−0.40	90.48	0.82	0.79
[−10, −8]	−32.15	−1.06	−1.04	−38.02	−0.76	−0.75	68.39	0.62	0.61
[−10, −7]	−22.46	−0.74	−0.73	−24.82	−0.49	−0.49	107.86	0.97	0.96
[−10, −6]	−46.17	−1.52	−1.48	−24.58	−0.49	−0.48	44.04	0.40	0.39
[−10, −5]	−43.22	−1.42	−1.40	−35.06	−0.70	−0.69	33.29	0.30	0.30
[−10, −4]	−32.33	−1.07	−1.05	−57.83	−1.15	−1.14	54.64	0.49	0.49
[−10, −3]	−35.86	−1.18	−1.16	−41.52	−0.83	−0.81	60.03	0.54	0.53
[−10, −2]	−24.43	−0.81	−0.79	−45.29	−0.90	−0.89	127.28	1.15	1.13
[−10, −1]	−31.38	−1.03	−1.00	−56.59	−1.13	−1.09	−152.70	−1.38	−1.33
[−10, 0]	−31.43	−1.04	−1.01	−41.73	−0.83	−0.81	−145.95	−1.32	−1.28
[−10, 1]	−27.72	−0.91	−0.90	−34.15	−0.68	−0.67	−59.50	−0.54	−0.53
[−10, 2]	−34.10	−1.12	−1.11	−54.90	−1.09	−1.08	126.28	1.14	1.12
[−10, 3]	−36.18	−1.19	−1.17	−72.73	−1.45	−1.43	−17.11	−0.15	−0.15
[−10, 4]	−21.72	−0.72	−0.70	−53.07	−1.06	−1.04	31.14	0.28	0.28
[−10, 5]	−5.53	−0.18	−0.18	−51.78	−1.03	−1.01	11.37	0.10	0.10
[−10, 6]	−24.33	−0.80	−0.79	−75.59	−1.51	−1.48	−56.00	−0.51	−0.50
[−10, 7]	−27.35	−0.90	−0.89	−64.98	−1.30	−1.28	−47.93	−0.43	−0.43
[−10, 8]	−37.83	−1.25	−1.23	−57.93	−1.15	−1.14	−42.76	−0.39	−0.38
[−10, 9]	−53.09	−1.75	−1.72	−66.45	−1.32	−1.30	151.09	1.37	1.34
[−10, 10]	−53.48	−1.76	−1.74	−68.55	−1.37	−1.35	32.85	0.30	0.29
[−10, 11]	−60.29	−1.99	−1.96	−76.02	−1.52	−1.49	41.99	0.38	0.37
[−10, 12]	−64.41	−2.12	−2.09	−65.83	−1.31	−1.29	−78.00	−0.70	−0.69
[−10, 13]	−67.75	−2.23	−2.19	−60.50	−1.21	−1.18	−195.37	−1.77	−1.73
[−10, 14]	−39.14	−1.29	−1.23	−17.27	−0.34	−0.33	−94.16	−0.85	−0.81
[−10, 15]	−66.85	−2.20	−2.14	22.58	0.45	0.44	−95.37	−0.86	−0.84
[−10, 16]	−64.64	−2.13	−2.08	−31.02	−0.62	−0.60	−125.22	−1.13	−1.11
[−10, 17]	−65.19	−2.15	−2.10	−77.12	−1.54	−1.50	1.41	0.01	0.01
[−10, 18]	−65.72	−2.17	−2.13	−59.58	−1.19	−1.17	−62.30	−0.56	−0.55
[−10, 19]	−42.09	−1.39	−1.37	−36.61	−0.73	−0.72	−179.05	−1.62	−1.59
[−10, 20]	−36.01	−1.19	−1.16	−44.92	−0.90	−0.88	−159.05	−1.44	−1.41

Table A19. Case V: GJR(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period $[\tau_1, \tau_2]$	**Group-Type**			**Individual-Type**			**Medical-Type**		
	CAR	**t-Value**		**CAR**	**t-Value**		**CAR**	**t-Value**	
		TM	**SRM**		**TM**	**SRM**		**TM**	**SRM**
[−10, −10]	−34.20	−0.62	−0.61	−14.18	−0.35	−0.35	73.79	0.25	0.25
[−10, −9]	−32.38	−0.59	−0.56	−16.97	−0.42	−0.41	113.70	0.39	0.38
[−10, −8]	−39.65	−0.72	−0.71	−33.24	−0.83	−0.81	102.96	0.35	0.35
[−10, −7]	−32.81	−0.59	−0.58	−17.93	−0.45	−0.44	154.09	0.53	0.52
[−10, −6]	−57.97	−1.05	−1.02	−17.71	−0.44	−0.43	101.39	0.35	0.34
[−10, −5]	−57.31	−1.04	−1.02	−26.91	−0.67	−0.66	102.09	0.35	0.34
[−10, −4]	−48.76	−0.88	−0.87	−48.32	−1.20	−1.18	134.90	0.46	0.46
[−10, −3]	−54.47	−0.98	−0.97	−30.92	−0.77	−0.76	151.69	0.52	0.51
[−10, −2]	−45.79	−0.83	−0.81	−32.72	−0.81	−0.80	230.56	0.79	0.78
[−10, −1]	−56.32	−1.02	−0.98	−40.78	−1.01	−0.98	−37.48	−0.13	−0.12
[−10, 0]	−57.71	−1.04	−1.01	−26.10	−0.65	−0.63	−19.65	−0.07	−0.07
[−10, 1]	−56.05	−1.01	−1.00	−17.63	−0.44	−0.43	78.15	0.27	0.26
[−10, 2]	−64.72	−1.17	−1.15	−37.10	−0.92	−0.91	275.38	0.94	0.93
[−10, 3]	−69.04	−1.25	−1.23	−53.76	−1.34	−1.32	143.41	0.49	0.48
[−10, 4]	−56.39	−1.02	−1.00	−33.56	−0.83	−0.82	202.92	0.70	0.68
[−10, 5]	−43.19	−0.78	−0.76	−29.92	−0.74	−0.73	194.86	0.67	0.65
[−10, 6]	−64.57	−1.17	−1.15	−52.02	−1.29	−1.27	139.04	0.48	0.47
[−10, 7]	−70.09	−1.27	−1.25	−39.82	−0.99	−0.97	158.64	0.54	0.54
[−10, 8]	−82.72	−1.50	−1.47	−31.72	−0.79	−0.78	175.20	0.60	0.59
[−10, 9]	−100.26	−1.81	−1.78	−38.97	−0.97	−0.95	380.49	1.31	1.29
[−10, 10]	−103.00	−1.86	−1.83	−39.71	−0.99	−0.97	273.72	0.94	0.92
[−10, 11]	−112.42	−2.03	−2.00	−45.43	−1.13	−1.11	294.42	1.01	0.99
[−10, 12]	−119.05	−2.15	−2.12	−33.63	−0.84	−0.82	185.96	0.64	0.63
[−10, 13]	−124.19	−2.24	−2.20	−27.79	−0.69	−0.68	79.84	0.27	0.27
[−10, 14]	−99.44	−1.80	−1.72	19.10	0.47	0.45	193.09	0.66	0.63
[−10, 15]	−128.41	−2.32	−2.25	58.65	1.46	1.41	202.93	0.70	0.68
[−10, 16]	−127.80	−2.31	−2.26	5.27	0.13	0.13	184.26	0.63	0.62
[−10, 17]	−129.95	−2.35	−2.30	−40.63	−1.01	−0.99	322.07	1.11	1.08
[−10, 18]	−132.77	−2.40	−2.36	−21.82	−0.54	−0.53	269.81	0.93	0.91
[−10, 19]	−111.73	−2.02	−1.99	2.88	0.07	0.07	164.61	0.56	0.56
[−10, 20]	−108.56	−1.96	−1.92	−3.20	−0.08	−0.08	196.30	0.67	0.66

Table A20. Case V: EGARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period $[\tau_1, \tau_2]$	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[−10, −10]	−34.56	−0.46	−0.45	−14.24	−0.34	−0.34	74.59	0.24	0.23
[−10, −9]	−34.31	−0.46	−0.44	−16.37	−0.40	−0.38	115.61	0.37	0.35
[−10, −8]	−42.11	−0.56	−0.56	−32.60	−0.79	−0.78	105.72	0.33	0.33
[−10, −7]	−36.31	−0.49	−0.48	−16.94	−0.41	−0.40	157.82	0.50	0.49
[−10, −6]	−61.59	−0.83	−0.80	−16.91	−0.41	−0.40	105.86	0.33	0.33
[−10, −5]	−61.62	−0.83	−0.81	−25.99	−0.63	−0.62	107.45	0.34	0.33
[−10, −4]	−53.78	−0.72	−0.71	−47.24	−1.14	−1.13	141.15	0.45	0.44
[−10, −3]	−60.10	−0.81	−0.79	−29.75	−0.72	−0.71	158.80	0.50	0.49
[−10, −2]	−52.40	−0.70	−0.69	−31.25	−0.76	−0.74	238.63	0.76	0.74
[−10, −1]	−64.46	−0.86	−0.83	−38.67	−0.94	−0.90	−28.30	−0.09	−0.09
[−10, 0]	−65.90	−0.88	−0.86	−24.23	−0.59	−0.57	−9.75	−0.03	−0.03
[−10, 1]	−64.75	−0.87	−0.85	−15.72	−0.38	−0.37	88.89	0.28	0.28
[−10, 2]	−74.11	−0.99	−0.98	−35.06	−0.85	−0.84	287.00	0.91	0.89
[−10, 3]	−79.07	−1.06	−1.04	−51.60	−1.25	−1.23	155.91	0.49	0.49
[−10, 4]	−66.77	−0.90	−0.88	−31.46	−0.76	−0.75	216.22	0.68	0.67
[−10, 5]	−54.72	−0.73	−0.72	−27.42	−0.66	−0.65	209.16	0.66	0.65
[−10, 6]	−76.97	−1.03	−1.02	−49.28	−1.19	−1.18	154.27	0.49	0.48
[−10, 7]	−83.31	−1.12	−1.10	−36.87	−0.89	−0.88	174.79	0.55	0.54
[−10, 8]	−96.52	−1.29	−1.27	−28.69	−0.70	−0.68	192.21	0.61	0.60
[−10, 9]	−114.74	−1.54	−1.52	−35.81	−0.87	−0.85	398.38	1.26	1.24
[−10, 10]	−118.20	−1.59	−1.56	−36.39	−0.88	−0.87	292.50	0.93	0.91
[−10, 11]	−128.51	−1.72	−1.70	−41.85	−1.01	−1.00	314.15	0.99	0.98
[−10, 12]	−135.96	−1.82	−1.79	−29.84	−0.72	−0.71	206.61	0.65	0.64
[−10, 13]	−141.45	−1.90	−1.86	−24.06	−0.58	−0.57	101.28	0.32	0.31
[−10, 14]	−118.41	−1.59	−1.52	23.57	0.57	0.55	215.68	0.68	0.65
[−10, 15]	−147.38	−1.98	−1.92	62.85	1.52	1.48	226.24	0.72	0.69
[−10, 16]	−146.99	−1.97	−1.93	9.33	0.23	0.22	208.33	0.66	0.64
[−10, 17]	−149.36	−2.00	−1.96	−36.71	−0.89	−0.87	346.90	1.10	1.07
[−10, 18]	−152.86	−2.05	−2.02	−17.76	−0.43	−0.42	295.52	0.94	0.92
[−10, 19]	−132.70	−1.78	−1.75	7.19	0.17	0.17	191.26	0.61	0.60
[−10, 20]	−130.63	−1.75	−1.72	1.48	0.04	0.04	223.94	0.71	0.69

Table A21. Case VI: OLS—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period $[\tau_1, \tau_2]$	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[−10, −10]	−24.32	−0.81	−0.80	7.76	0.30	0.29	−70.72	−0.86	−0.85
[−10, −9]	10.40	0.35	0.34	58.26	2.25	2.21	−25.18	−0.31	−0.30
[−10, −8]	−11.30	−0.38	−0.37	65.74	2.53	2.47	−92.40	−1.12	−1.10
[−10, −7]	−21.85	−0.73	−0.72	17.20	0.66	0.65	−173.94	−2.12	−2.08
[−10, −6]	5.36	0.18	0.18	−9.47	−0.36	−0.36	−176.40	−2.15	−2.11
[−10, −5]	1.89	0.06	0.06	−25.76	−0.99	−0.98	−171.38	−2.09	−2.05
[−10, −4]	−70.65	−2.36	−2.33	−55.13	−2.13	−2.09	−280.66	−3.42*	−3.36*
[−10, −3]	−1.99	−0.07	−0.06	1.47	0.06	0.05	−237.28	−2.89	−2.78
[−10, −2]	30.52	1.02	1.00	14.08	0.54	0.53	−240.59	−2.93*	−2.87
[−10, −1]	9.21	0.31	0.30	−47.44	−1.83	−1.80	−164.63	−2.00	−1.97
[−10, 0]	30.07	1.01	0.98	12.36	0.48	0.47	−138.47	−1.69	−1.65
[−10, 1]	57.50	1.92	1.89	22.56	0.87	0.86	−47.02	−0.57	−0.56
[−10, 2]	76.82	2.57	2.53	21.41	0.83	0.81	−28.55	−0.35	−0.34
[−10, 3]	85.86	2.87	2.81	6.47	0.25	0.24	−23.41	−0.28	−0.28
[−10, 4]	16.91	0.57	0.53	−26.98	−1.04	−0.98	−209.17	−2.55	−2.41
[−10, 5]	41.20	1.38	1.36	37.75	1.46	1.43	−188.17	−2.29	−2.26
[−10, 6]	1.79	0.06	0.06	55.76	2.15	2.12	−189.74	−2.31	−2.27
[−10, 7]	24.03	0.80	0.79	21.28	0.82	0.81	−55.95	−0.68	−0.67
[−10, 8]	−4.04	−0.14	−0.13	22.59	0.87	0.86	−231.67	−2.82	−2.78
[−10, 9]	−35.66	−1.19	−0.72	−16.96	−0.65	−0.40	−205.18	−2.50	−1.51
[−10, 10]	38.92	1.30	1.25	110.78	4.27 *	4.10 *	−54.61	−0.66	−0.64
[−10, 11]	38.62	1.29	1.25	142.38	5.49 **	5.32 **	−49.38	−0.60	−0.58
[−10, 12]	77.89	2.60	2.55	184.77	7.12 **	6.96 **	−56.23	−0.68	−0.67
[−10, 13]	102.38	3.42 *	3.34 *	197.50	7.61 **	7.43 **	−30.23	−0.37	−0.36
[−10, 14]	81.26	2.72	2.66	176.59	6.81 **	6.67 **	−107.71	−1.31	−1.29
[−10, 15]	14.57	0.49	0.48	121.64	4.69 **	4.61 **	−114.08	−1.39	−1.37
[−10, 16]	12.02	0.40	0.40	98.97	3.81 *	3.76 *	−75.79	−0.92	−0.91
[−10, 17]	0.16	0.01	0.01	52.26	2.01	1.98	−77.20	−0.94	−0.93
[−10, 18]	−31.51	−1.05	−1.03	−9.70	−0.37	−0.37	−52.78	−0.64	−0.63
[−10, 19]	−42.43	−1.42	−1.37	−31.32	−1.21	−1.16	−136.38	−1.66	−1.60
[−10, 20]	−54.12	−1.81	−1.71	−84.43	−3.25	−3.08	−222.72	−2.71	−2.56

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A22. Case VI: GARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period $[\tau_1, \tau_2]$	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[−10,−10]	−24.57	−0.78	−0.77	10.83	0.24	0.24	−66.73	−0.51	−0.50
[−10,−9]	9.91	0.31	0.31	62.18	1.39	1.36	−17.66	−0.13	−0.13
[−10,−8]	−12.05	−0.38	−0.37	74.04	1.65	1.61	−80.61	−0.61	−0.60
[−10,−7]	−22.82	−0.72	−0.71	22.98	0.51	0.50	−159.34	−1.21	−1.19
[−10,−6]	4.15	0.13	0.13	−5.55	−0.12	−0.12	−158.84	−1.21	−1.19
[−10,−5]	0.42	0.01	0.01	−18.30	−0.41	−0.40	−149.72	−1.14	−1.12
[−10,−4]	−72.35	−2.30	−2.26	−46.54	−1.04	−1.02	−255.42	−1.94	−1.91
[−10,−3]	−3.97	−0.13	−0.12	19.43	0.43	0.42	−206.73	−1.57	−1.51
[−10,−2]	28.32	0.90	0.88	27.67	0.62	0.61	−207.60	−1.58	−1.55
[−10,−1]	6.78	0.22	0.21	−37.33	−0.83	−0.82	−129.02	−0.98	−0.96
[−10,0]	27.40	0.87	0.85	20.12	0.45	0.44	−100.01	−0.76	−0.74
[−10,1]	54.58	1.73	1.71	34.78	0.78	0.76	−4.27	−0.03	−0.03
[−10,2]	73.65	2.34	2.30	37.81	0.84	0.83	18.42	0.14	0.14
[−10,3]	82.44	2.62	2.56	27.67	0.62	0.60	27.92	0.21	0.21
[−10,4]	13.22	0.42	0.40	2.63	0.06	0.06	−152.73	−1.16	−1.10
[−10,5]	37.30	1.18	1.17	57.25	1.28	1.26	−130.50	−0.99	−0.98
[−10,6]	−2.36	−0.07	−0.07	77.33	1.73	1.70	−128.29	−0.97	−0.96
[−10,7]	19.64	0.62	0.61	45.04	1.00	0.99	9.32	0.07	0.07
[−10,8]	−8.67	−0.28	−0.27	46.25	1.03	1.02	−163.08	−1.24	−1.22
[−10,9]	−40.38	−1.28	−0.77	−46.82	−1.04	−0.63	−144.47	−1.10	−0.66
[−10,10]	33.77	1.07	1.03	145.33	3.24 *	3.11 *	22.96	0.17	0.17
[−10,11]	33.24	1.06	1.02	176.07	3.93 *	3.81 *	31.36	0.24	0.23
[−10,12]	72.28	2.30	2.24	217.51	4.85 **	4.74 **	27.66	0.21	0.21
[−10,13]	96.52	3.07 *	2.99 *	231.88	5.17 **	5.05 **	57.36	0.44	0.43
[−10,14]	75.16	2.39	2.34	210.81	4.70 **	4.61 **	−16.81	−0.13	−0.13
[−10,15]	8.23	0.26	0.26	155.46	3.47 *	3.41 *	−19.92	−0.15	−0.15
[−10,16]	5.45	0.17	0.17	130.98	2.92 *	2.88	21.34	0.16	0.16
[−10,17]	−6.66	−0.21	−0.21	85.37	1.90	1.88	23.51	0.18	0.18
[−10,18]	−38.59	−1.23	−1.20	29.29	0.65	0.64	52.51	0.40	0.39
[−10,19]	−49.77	−1.58	−1.52	13.92	0.31	0.30	−26.42	−0.20	−0.19
[−10,20]	−61.71	−1.96	−1.85	−34.58	−0.77	−0.73	−108.45	−0.82	−0.78

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A23. Case VI: GJR(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[−10, −10]	−21.70	−0.33	−0.32	11.64	0.17	0.17	−61.71	−0.24	−0.23
[−10, −9]	15.06	0.23	0.22	63.98	0.93	0.91	−7.62	−0.03	−0.03
[−10, −8]	−3.67	−0.06	−0.05	76.55	1.11	1.08	−65.54	−0.25	−0.24
[−10, −7]	−13.08	−0.20	−0.19	26.72	0.39	0.38	−139.27	−0.53	−0.52
[−10, −6]	15.44	0.23	0.23	−0.62	−0.01	−0.01	−133.77	−0.51	−0.50
[−10, −5]	14.72	0.22	0.22	−12.60	−0.18	−0.18	−119.63	−0.46	−0.45
[−10, −4]	−55.71	−0.84	−0.83	−39.88	−0.58	−0.57	−220.31	−0.84	−0.83
[−10, −3]	17.24	0.26	0.25	26.42	0.38	0.37	−166.56	−0.64	−0.61
[−10, −2]	50.40	0.76	0.75	36.04	0.52	0.51	−162.44	−0.62	−0.61
[−10, −1]	29.98	0.45	0.45	−27.65	−0.40	−0.39	−78.88	−0.30	−0.30
[−10, 0]	52.02	0.79	0.77	31.02	0.45	0.44	−44.87	−0.17	−0.17
[−10, 1]	82.44	1.25	1.23	46.39	0.67	0.66	55.90	0.21	0.21
[−10, 2]	104.68	1.58	1.56	50.15	0.73	0.71	83.63	0.32	0.31
[−10, 3]	116.81	1.77	1.73	40.69	0.59	0.58	98.16	0.38	0.37
[−10, 4]	51.89	0.78	0.74	16.05	0.23	0.22	−77.44	−0.30	−0.28
[−10, 5]	75.31	1.14	1.12	72.48	1.05	1.03	−50.25	−0.19	−0.19
[−10, 6]	38.26	0.58	0.57	93.45	1.35	1.33	−43.02	−0.16	−0.16
[−10, 7]	62.89	0.95	0.93	62.04	0.90	0.88	99.61	0.38	0.37
[−10, 8]	36.60	0.55	0.54	64.30	0.93	0.92	−67.78	−0.26	−0.26
[−10, 9]	−7.40	−0.11	−0.07	−23.68	−0.34	−0.21	−44.44	−0.17	−0.10
[−10, 10]	86.06	1.30	1.25	164.65	2.38	2.29	128.34	0.49	0.47
[−10, 11]	87.35	1.32	1.28	196.49	2.84	2.76	141.74	0.54	0.53
[−10, 12]	128.18	1.94	1.89	239.06	3.46 *	3.38 *	143.05	0.55	0.53
[−10, 13]	154.92	2.34	2.29	254.35	3.68 *	3.59 *	177.76	0.68	0.66
[−10, 14]	135.56	2.05	2.01	234.33	3.39 *	3.32 *	108.60	0.42	0.41
[−10, 15]	70.57	1.07	1.05	180.05	2.61	2.56	110.50	0.42	0.42
[−10, 16]	69.35	1.05	1.03	156.75	2.27	2.23	156.76	0.60	0.59
[−10, 17]	59.59	0.90	0.89	112.11	1.62	1.60	163.95	0.63	0.62
[−10, 18]	31.29	0.47	0.46	56.62	0.82	0.80	197.99	0.76	0.74
[−10, 19]	23.83	0.36	0.35	41.82	0.61	0.58	124.09	0.47	0.46
[−10, 20]	15.18	0.23	0.22	−5.97	−0.09	−0.08	47.10	0.18	0.17

Note: * denotes significance at the 10% level.

Table A24. Case VI: EGARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	**Group-Type**			**Individual-Type**			**Medical-Type**		
	CAR	**t-Value**		**CAR**	**t-Value**		**CAR**	**t-Value**	
		TM	**SRM**		**TM**	**SRM**		**TM**	**SRM**
[−10, −10]	−21.43	−0.27	−0.26	11.60	0.16	0.16	−55.27	−0.12	−0.12
[−10, −9]	15.90	0.20	0.20	64.02	0.91	0.89	5.84	0.01	0.01
[−10, −8]	−2.74	−0.03	−0.03	76.48	1.08	1.06	−46.00	−0.10	−0.10
[−10, −7]	−11.11	−0.14	−0.14	26.91	0.38	0.37	−111.80	−0.25	−0.24
[−10, −6]	18.35	0.23	0.23	−0.20	0.00	0.00	−98.54	−0.22	−0.21
[−10, −5]	17.83	0.22	0.22	−12.24	−0.17	−0.17	−78.09	−0.17	−0.17
[−10, −4]	−52.06	−0.65	−0.64	−39.45	−0.56	−0.55	−171.82	−0.38	−0.37
[−10, −3]	20.29	0.25	0.24	26.46	0.37	0.36	−113.33	−0.25	−0.24
[−10, −2]	54.74	0.69	0.67	36.44	0.52	0.51	−100.79	−0.22	−0.22
[−10, −1]	35.49	0.45	0.44	−26.92	−0.38	−0.38	−9.04	−0.02	−0.02
[−10, 0]	58.54	0.73	0.72	32.00	0.45	0.44	32.86	0.07	0.07
[−10, 1]	89.04	1.12	1.10	47.26	0.67	0.66	139.69	0.31	0.30
[−10, 2]	111.40	1.40	1.38	50.92	0.72	0.71	173.55	0.38	0.37
[−10, 3]	123.55	1.55	1.52	41.32	0.58	0.57	194.05	0.43	0.42
[−10, 4]	58.17	0.73	0.69	16.35	0.23	0.22	23.45	0.05	0.05
[−10, 5]	83.67	1.05	1.03	73.47	1.04	1.02	60.61	0.13	0.13
[−10, 6]	47.02	0.59	0.58	94.45	1.34	1.32	74.54	0.16	0.16
[−10, 7]	72.04	0.90	0.89	63.04	0.89	0.88	223.83	0.49	0.48
[−10, 8]	46.46	0.58	0.57	65.44	0.93	0.91	63.72	0.14	0.14
[−10, 9]	10.50	0.13	0.08	−19.46	−0.28	−0.17	108.67	0.24	0.14
[−10, 10]	95.80	1.20	1.15	165.44	2.34	2.25	271.43	0.59	0.57
[−10, 11]	97.89	1.23	1.19	197.46	2.80	2.71	292.32	0.64	0.62
[−10, 12]	139.55	1.75	1.71	240.21	3.40 *	3.32 *	301.14	0.66	0.65
[−10, 13]	166.74	2.09	2.04	255.53	3.62 *	3.53 *	342.66	0.75	0.73
[−10, 14]	148.10	1.86	1.82	235.65	3.34 *	3.27 *	280.81	0.62	0.60
[−10, 15]	83.85	1.05	1.03	181.53	2.57	2.53	290.07	0.64	0.63
[−10, 16]	83.58	1.05	1.03	158.46	2.24	2.21	344.07	0.75	0.74
[−10, 17]	74.36	0.93	0.92	113.88	1.61	1.59	358.22	0.79	0.77
[−10, 18]	45.93	0.58	0.57	58.20	0.82	0.81	397.93	0.87	0.86
[−10, 19]	38.31	0.48	0.46	43.18	0.61	0.59	329.62	0.72	0.70
[−10, 20]	29.71	0.37	0.35	−4.74	−0.07	−0.06	258.64	0.57	0.54

Note: * denotes significance at the 10% level.

Table A25. Case VII: OLS—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	−17.29	−0.88	−0.86	6.24	0.27	0.26	176.65	2.15	2.11
[0, 1]	−20.93	−1.06	−1.05	37.49	1.60	1.58	233.85	2.84	2.80
[0, 2]	0.56	0.03	0.03	47.07	2.01	1.98	53.96	0.66	0.65
[0, 3]	−28.25	−1.43	−1.41	23.73	1.02	1.00	227.76	2.77	2.73
[0, 4]	−34.92	−1.77	−1.74	11.10	0.47	0.47	138.31	1.68	1.66
[0, 5]	−9.64	−0.49	−0.48	20.04	0.86	0.84	256.74	3.12 *	3.07 *
[0, 6]	0.01	0.00	0.00	16.08	0.69	0.68	187.34	2.28	2.24
[0, 7]	6.44	0.33	0.32	13.94	0.60	0.59	281.62	3.42 *	3.37 *
[0, 8]	7.16	0.36	0.36	42.80	1.83	1.80	259.33	3.15 *	3.10 *
[0, 9]	16.77	0.85	0.84	52.25	2.24	2.20	309.96	3.77 *	3.71 *
[0, 10]	−21.75	−1.10	−1.09	20.16	0.86	0.85	213.71	2.60	2.56
[0, 11]	−23.03	−1.17	−1.15	11.32	0.48	0.48	265.44	3.23 *	3.18 *
[0, 12]	−4.07	−0.21	−0.20	10.95	0.47	0.46	110.16	1.34	1.32
[0, 13]	7.58	0.38	0.38	15.90	0.68	0.67	193.00	2.35	2.30
[0, 14]	16.32	0.83	0.82	19.06	0.82	0.80	198.66	2.41	2.38
[0, 15]	9.57	0.49	0.47	39.59	1.69	1.65	234.78	2.85	2.79
[0, 16]	21.61	1.10	1.08	37.16	1.59	1.56	282.05	3.43 *	3.37 *
[0, 17]	−30.99	−1.57	−1.55	3.80	0.16	0.16	222.94	2.71	2.67
[0, 18]	−18.37	−0.93	−0.92	−1.60	−0.07	−0.07	274.04	3.33 *	3.28 *
[0, 19]	−22.77	−1.16	−1.14	−11.07	−0.47	−0.47	303.07	3.68 *	3.62 *
[0, 20]	1.76	0.09	0.09	−4.33	−0.19	−0.18	327.69	3.98 *	3.92 *
[0, 21]	−5.85	−0.30	−0.29	−10.32	−0.44	−0.43	212.75	2.59	2.55
[0, 22]	7.78	0.39	0.39	2.08	0.09	0.09	177.01	2.15	2.12
[0, 23]	−0.50	−0.03	−0.02	−11.78	−0.50	−0.50	207.81	2.53	2.49
[0, 24]	−54.74	−2.78	−2.74	−30.23	−1.29	−1.27	231.82	2.82	2.77
[0, 25]	−77.00	−3.91 *	−3.85 *	−57.37	−2.45	−2.42	311.12	3.78 *	3.72 *
[0, 26]	−62.26	−3.16 *	−3.11 *	−74.21	−3.17 *	−3.12 *	188.75	2.29	2.26
[0, 27]	−43.88	−2.23	−2.19	−89.98	−3.85 *	−3.79 *	309.29	3.76 *	3.70 *
[0, 28]	−45.40	−2.30	−2.27	−75.29	−3.22 *	−3.17 *	284.92	3.46 *	3.41 *
[0, 29]	−42.96	−2.18	−2.14	−62.63	−2.68	−2.63	391.41	4.76 **	4.68 **
[0, 30]	−47.64	−2.42	−2.38	−62.01	−2.65	−2.61	357.44	4.34 **	4.28 *

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A26. Case VII: GARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period $[\tau_1, \tau_2]$	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	−18.31	−0.54	−0.53	5.71	0.20	0.20	176.75	2.11	2.08
[0, 1]	−23.24	−0.68	−0.67	36.48	1.29	1.27	234.01	2.80	2.76
[0, 2]	−2.57	−0.08	−0.07	45.51	1.61	1.58	54.24	0.65	0.64
[0, 3]	−32.35	−0.95	−0.94	21.63	0.76	0.75	228.14	2.73	2.69
[0, 4]	−39.96	−1.18	−1.16	8.46	0.30	0.29	138.78	1.66	1.63
[0, 5]	−16.17	−0.48	−0.47	16.95	0.60	0.59	257.26	3.08 *	3.03 *
[0, 6]	−7.72	−0.23	−0.22	12.49	0.44	0.43	187.93	2.25	2.21
[0, 7]	−2.18	−0.06	−0.06	9.80	0.35	0.34	282.33	3.38 *	3.32 *
[0, 8]	−2.75	−0.08	−0.08	38.18	1.35	1.33	260.11	3.11 *	3.06 *
[0, 9]	5.61	0.17	0.16	47.14	1.66	1.64	310.80	3.72 *	3.66 *
[0, 10]	−33.88	−1.00	−0.98	14.52	0.51	0.50	214.65	2.57	2.53
[0, 11]	−36.25	−1.07	−1.05	5.16	0.18	0.18	266.46	3.19 *	3.14 *
[0, 12]	−18.87	−0.56	−0.55	4.34	0.15	0.15	111.23	1.33	1.31
[0, 13]	−7.60	−0.22	−0.22	8.68	0.31	0.30	194.22	2.32	2.28
[0, 14]	−0.08	0.00	0.00	11.34	0.40	0.39	199.96	2.39	2.35
[0, 15]	−9.27	−0.27	−0.27	31.54	1.11	1.09	236.03	2.82	2.76
[0, 16]	1.98	0.06	0.06	28.56	1.01	0.99	283.41	3.39 *	3.33 *
[0, 17]	−51.32	−1.51	−1.49	−5.37	−0.19	−0.19	224.44	2.68	2.64
[0, 18]	−39.87	−1.17	−1.16	−11.28	−0.40	−0.39	275.61	3.30 *	3.25 *
[0, 19]	−46.02	−1.36	−1.33	−21.16	−0.75	−0.73	304.66	3.64 *	3.58 *
[0, 20]	−22.37	−0.66	−0.65	−14.97	−0.53	−0.52	329.39	3.94 *	3.88 *
[0, 21]	−30.93	−0.91	−0.90	−21.49	−0.76	−0.75	214.56	2.57	2.53
[0, 22]	−18.96	−0.56	−0.55	−9.53	−0.34	−0.33	178.85	2.14	2.10
[0, 23]	−28.40	−0.84	−0.82	−23.89	−0.84	−0.83	209.72	2.51	2.47
[0, 24]	−83.61	−2.46	−2.42	−42.88	−1.51	−1.49	233.84	2.80	2.75
[0, 25]	−106.71	−3.14 *	−3.09 *	−70.57	−2.49	−2.45	313.24	3.75 *	3.69 *
[0, 26]	−93.56	−2.76	−2.71	−87.85	−3.10 *	−3.05 *	190.91	2.28	2.25
[0, 27]	−76.17	−2.24	−2.21	−104.15	−3.67 *	−3.62 *	311.54	3.73 *	3.67 *
[0, 28]	−78.85	−2.32	−2.29	−89.97	−3.17 *	−3.13 *	287.26	3.43 *	3.38 *
[0, 29]	−78.12	−2.30	−2.26	−77.73	−2.74	−2.70	393.77	4.71 **	4.63 **
[0, 30]	−84.34	−2.48	−2.44	−77.56	−2.74	−2.69	359.84	4.30 *	4.23 *

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A27. Case VII: GJR(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period $[\tau_1, \tau_2]$	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	−17.09	−0.81	−0.79	6.27	0.27	0.26	178.17	1.56	1.54
[0, 1]	−20.64	−0.97	−0.96	37.61	1.61	1.59	236.91	2.08	2.04
[0, 2]	1.12	0.05	0.05	47.19	2.02	1.99	58.52	0.51	0.50
[0, 3]	−27.47	−1.30	−1.28	23.87	1.02	1.01	233.84	2.05	2.02
[0, 4]	−33.91	−1.60	−1.57	11.25	0.48	0.47	145.90	1.28	1.26
[0, 5]	−8.62	−0.41	−0.40	20.32	0.87	0.86	265.89	2.33	2.29
[0, 6]	1.16	0.05	0.05	16.43	0.70	0.69	198.02	1.73	1.71
[0, 7]	7.84	0.37	0.36	14.30	0.61	0.60	293.81	2.57	2.53
[0, 8]	8.65	0.41	0.40	43.25	1.85	1.82	273.07	2.39	2.36
[0, 9]	18.37	0.87	0.85	52.77	2.26	2.23	325.24	2.85	2.81
[0, 10]	−19.94	−0.94	−0.93	20.71	0.89	0.87	230.50	2.02	1.99
[0, 11]	−21.05	−0.99	−0.98	11.91	0.51	0.50	283.75	2.49	2.45
[0, 12]	−2.11	−0.10	−0.10	11.68	0.50	0.49	130.05	1.14	1.12
[0, 13]	9.99	0.47	0.46	16.55	0.71	0.70	214.34	1.88	1.84
[0, 14]	18.85	0.89	0.88	19.77	0.85	0.83	221.55	1.94	1.91
[0, 15]	11.73	0.55	0.54	40.61	1.74	1.70	259.31	2.27	2.22
[0, 16]	24.06	1.13	1.12	38.17	1.64	1.61	308.08	2.70	2.66
[0, 17]	−28.21	−1.33	−1.31	4.79	0.21	0.20	250.47	2.19	2.16
[0, 18]	−15.45	−0.73	−0.72	−0.56	−0.02	−0.02	303.09	2.66	2.62
[0, 19]	−19.95	−0.94	−0.92	−9.85	−0.42	−0.41	333.71	2.92*	2.87
[0, 20]	4.84	0.23	0.22	−3.10	−0.13	−0.13	359.83	3.15*	3.10*
[0, 21]	−2.55	−0.12	−0.12	−9.07	−0.39	−0.38	246.41	2.16	2.13
[0, 22]	11.02	0.52	0.51	3.48	0.15	0.15	212.25	1.86	1.83
[0, 23]	2.89	0.14	0.13	−10.31	−0.44	−0.44	244.58	2.14	2.11
[0, 24]	−51.14	−2.41	−2.37	−28.74	−1.23	−1.21	270.10	2.37	2.33
[0, 25]	−73.13	−3.45 *	−3.39 *	−55.88	−2.39	−2.36	350.90	3.07 *	3.03 *
[0, 26]	−58.41	−2.75	−2.71	−72.58	−3.11 *	−3.06 *	230.10	2.02	1.98
[0, 27]	−39.82	−1.88	−1.85	−88.32	−3.78 *	−3.73 *	352.16	3.09 *	3.04 *
[0, 28]	−41.21	−1.94	−1.91	−73.57	−3.15 *	−3.10 *	329.32	2.89	2.84
[0, 29]	−38.85	−1.83	−1.80	−60.74	−2.60	−2.56	437.39	3.83 *	3.77 *
[0, 30]	−43.53	−2.05	−2.02	−59.98	−2.57	−2.53	404.99	3.55 *	3.49 *

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A28. Case VII: EGARCH(1,1)–Cumulative Abnormal Change Rate of Chinese Tourist Arrivals.

Event Period [τ_1, τ_2]	**Group-Type**			**Individual-Type**			**Medical-Type**		
	CAR	**t-Value**		**CAR**	**t-Value**		**CAR**	**t-Value**	
		TM	**SRM**		**TM**	**SRM**		**TM**	**SRM**
[0, 0]	−16.75	−0.53	−0.53	6.32	0.27	0.27	178.17	0.51	0.50
[0, 1]	−19.62	−0.63	−0.62	37.74	1.61	1.58	236.91	0.67	0.66
[0, 2]	2.23	0.07	0.07	47.34	2.02	1.99	58.52	0.17	0.16
[0, 3]	−26.08	−0.83	−0.82	24.06	1.03	1.01	233.84	0.66	0.65
[0, 4]	−32.28	−1.03	−1.01	11.48	0.49	0.48	145.90	0.41	0.41
[0, 5]	−6.05	−0.19	−0.19	20.66	0.88	0.87	265.89	0.75	0.74
[0, 6]	4.30	0.14	0.14	16.85	0.72	0.71	198.02	0.56	0.55
[0, 7]	11.15	0.36	0.35	14.74	0.63	0.62	293.81	0.83	0.82
[0, 8]	12.64	0.40	0.40	43.77	1.87	1.84	273.07	0.77	0.76
[0, 9]	23.00	0.73	0.72	53.38	2.28	2.24	325.24	0.92	0.91
[0, 10]	−15.02	−0.48	−0.47	21.36	0.91	0.90	230.50	0.65	0.64
[0, 11]	−15.71	−0.50	−0.49	12.62	0.54	0.53	283.75	0.80	0.79
[0, 12]	4.28	0.14	0.13	12.52	0.53	0.53	130.05	0.37	0.36
[0, 13]	15.92	0.51	0.50	17.34	0.74	0.73	214.34	0.61	0.60
[0, 14]	25.36	0.81	0.80	20.64	0.88	0.87	221.55	0.63	0.62
[0, 15]	20.37	0.65	0.63	41.73	1.78	1.74	259.31	0.74	0.72
[0, 16]	32.76	1.05	1.03	39.31	1.68	1.65	308.08	0.87	0.86
[0, 17]	−19.58	−0.63	−0.61	5.92	0.25	0.25	250.47	0.71	0.70
[0, 18]	−6.29	−0.20	−0.20	0.65	0.03	0.03	303.09	0.86	0.85
[0, 19]	−9.52	−0.30	−0.30	−8.49	−0.36	−0.36	333.71	0.95	0.93
[0, 20]	15.44	0.49	0.49	−1.72	−0.07	−0.07	359.83	1.02	1.00
[0, 21]	8.30	0.26	0.26	−7.65	−0.33	−0.32	246.41	0.70	0.69
[0, 22]	23.01	0.73	0.72	5.04	0.22	0.21	212.25	0.60	0.59
[0, 23]	15.41	0.49	0.48	−8.69	−0.37	−0.36	244.58	0.69	0.68
[0, 24]	−38.34	−1.22	−1.21	−27.07	−1.15	−1.14	270.10	0.77	0.75
[0, 25]	−60.23	−1.92	−1.89	−54.19	−2.31	−2.27	350.90	0.99	0.98
[0, 26]	−44.44	−1.42	−1.40	−70.76	−3.02 *	−2.97 *	230.10	0.65	0.64
[0, 27]	−25.55	−0.82	−0.80	−86.46	−3.69 *	−3.63 *	352.16	1.00	0.98
[0, 28]	−26.42	−0.84	−0.83	−71.64	−3.05 *	−3.01 *	329.32	0.93	0.92
[0, 29]	−22.84	−0.73	−0.72	−58.66	−2.50	−2.46	437.39	1.24	1.22
[0, 30]	−26.52	−0.85	−0.83	−57.78	−2.46	−2.42	404.99	1.15	1.13

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A29. Case VIII: OLS—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period $[\tau_1, \tau_2]$	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	4.72	0.21	0.20	9.73	0.31	0.30	26.95	0.25	0.24
[0, 1]	5.36	0.23	0.23	27.43	0.86	0.85	161.67	1.48	1.45
[0, 2]	25.92	1.13	1.11	28.94	0.91	0.90	94.68	0.86	0.85
[0, 3]	−8.18	−0.36	−0.35	−25.21	−0.79	−0.78	159.44	1.46	1.43
[0, 4]	10.22	0.45	0.44	−75.97	−2.39	−2.35	103.78	0.95	0.93
[0, 5]	38.10	1.66	1.63	−6.14	−0.19	−0.19	14.05	0.13	0.13
[0, 6]	72.00	3.14 *	3.09 *	6.18	0.19	0.19	106.84	0.98	0.96
[0, 7]	94.02	4.09 *	4.03 *	42.28	1.33	1.31	243.60	2.22	2.19
[0, 8]	75.79	3.30 *	3.25 *	39.93	1.26	1.24	129.57	1.18	1.16
[0, 9]	78.19	3.41 *	3.35 *	39.50	1.24	1.22	262.72	2.40	2.36
[0, 10]	37.63	1.64	1.61	0.74	0.02	0.02	225.73	2.06	2.03
[0, 11]	54.47	2.37	2.34	−4.25	−0.13	−0.13	80.91	0.74	0.73
[0, 12]	69.67	3.03 *	2.99 *	18.10	0.57	0.56	120.24	1.10	1.08
[0, 13]	88.94	3.87 *	3.81 *	14.16	0.45	0.44	226.26	2.07	2.03
[0, 14]	83.04	3.62 *	3.56 *	10.67	0.34	0.33	286.53	2.62	2.58
[0, 15]	109.07	4.75 **	4.67 **	37.86	1.19	1.17	212.78	1.94	1.91
[0, 16]	86.05	3.75 *	3.69 *	33.31	1.05	1.03	194.44	1.78	1.75
[0, 17]	11.28	0.49	0.48	−33.07	−1.04	−1.02	313.07	2.86	2.81
[0, 18]	97.33	4.24 *	4.17 *	45.76	1.44	1.42	280.25	2.56	2.52
[0, 19]	80.53	3.51 *	3.45 *	10.36	0.33	0.32	230.22	2.10	2.07
[0, 20]	73.53	3.20 *	3.15 *	27.48	0.87	0.85	115.74	1.06	1.04
[0, 21]	58.35	2.54	2.50	60.78	1.92	1.88	358.75	3.28 *	3.22 *
[0, 22]	44.11	1.92	1.89	79.54	2.51	2.47	363.99	3.32 *	3.27 *
[0, 23]	54.46	2.37	2.34	102.67	3.23 *	3.19 *	276.45	2.52	2.48
[0, 24]	37.85	1.65	1.62	92.36	2.91	2.86	320.12	2.92 *	2.88
[0, 25]	82.27	3.58 *	3.53 *	127.84	4.03 *	3.97 *	251.14	2.29	2.26
[0, 26]	62.06	2.70	2.66	168.10	5.30 **	5.21 **	212.45	1.94	1.91
[0, 27]	97.53	4.25 *	4.18 *	188.72	5.95 **	5.85 **	211.11	1.93	1.90
[0, 28]	78.33	3.41 *	3.36 *	162.72	5.13 **	5.05 **	174.28	1.59	1.57
[0, 29]	31.03	1.35	1.33	121.60	3.83 *	3.77 *	284.24	2.59	2.55
[0, 30]	25.77	1.12	1.10	56.03	1.77	1.74	116.45	1.06	1.05

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A30. Case VIII: GARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period $[\tau_1, \tau_2]$	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	4.75	0.21	0.20	9.47	0.32	0.31	30.58	0.15	0.15
[0, 1]	5.60	0.25	0.24	26.91	0.90	0.88	168.37	0.82	0.80
[0, 2]	26.54	1.16	1.14	28.17	0.94	0.92	103.94	0.50	0.49
[0, 3]	−8.18	−0.36	−0.35	−26.25	−0.88	−0.86	174.31	0.84	0.83
[0, 4]	10.94	0.48	0.47	−77.26	−2.58	−2.53	120.20	0.58	0.57
[0, 5]	38.71	1.69	1.67	−7.69	−0.26	−0.25	34.50	0.17	0.16
[0, 6]	72.61	3.18 *	3.13 *	4.37	0.15	0.14	130.99	0.63	0.62
[0, 7]	94.80	4.15 *	4.08 *	40.22	1.34	1.32	270.95	1.31	1.29
[0, 8]	76.46	3.34 *	3.29 *	37.60	1.25	1.24	161.01	0.78	0.77
[0, 9]	79.04	3.46 *	3.40 *	36.92	1.23	1.21	297.33	1.44	1.42
[0, 10]	38.33	1.68	1.65	−2.11	−0.07	−0.07	264.49	1.28	1.26
[0, 11]	55.16	2.41	2.38	−7.36	−0.25	−0.24	123.40	0.60	0.59
[0, 12]	70.43	3.08 *	3.03 *	14.73	0.49	0.48	166.25	0.81	0.79
[0, 13]	89.73	3.93 *	3.87 *	10.54	0.35	0.35	275.87	1.34	1.32
[0, 14]	83.79	3.67 *	3.61 *	6.78	0.23	0.22	340.00	1.65	1.62
[0, 15]	110.11	4.82 **	4.74 **	33.72	1.13	1.11	269.11	1.30	1.28
[0, 16]	87.00	3.81 *	3.75 *	28.91	0.96	0.95	254.73	1.23	1.22
[0, 17]	11.97	0.52	0.51	−37.73	−1.26	−1.24	377.86	1.83	1.80
[0, 18]	98.32	4.30 *	4.24 *	40.84	1.36	1.34	347.88	1.69	1.66
[0, 19]	81.48	3.56 *	3.51 *	5.18	0.17	0.17	301.66	1.46	1.44
[0, 20]	74.66	3.27 *	3.22 *	22.04	0.74	0.72	190.36	0.92	0.91
[0, 21]	59.65	2.61	2.57	55.09	1.84	1.81	436.57	2.11	2.08
[0, 22]	45.22	1.98	1.95	73.59	2.46	2.42	446.12	2.16	2.13
[0, 23]	55.57	2.43	2.39	96.45	3.22 *	3.17 *	362.27	1.75	1.73
[0, 24]	38.89	1.70	1.67	85.89	2.87	2.82	409.86	1.99	1.95
[0, 25]	83.50	3.65 *	3.60 *	121.10	4.04 *	3.98 *	344.06	1.67	1.64
[0, 26]	63.23	2.77	2.72	161.11	5.38 **	5.29 **	309.24	1.50	1.47
[0, 27]	99.02	4.33 *	4.26 *	181.47	6.06 **	5.96 **	310.68	1.50	1.48
[0, 28]	79.89	3.49 *	3.44 *	155.21	5.18 **	5.10 **	277.36	1.34	1.32
[0, 29]	32.68	1.43	1.41	113.84	3.80 *	3.74 *	390.76	1.89	1.86
[0, 30]	27.01	1.18	1.16	48.00	1.60	1.58	227.88	1.10	1.09

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A31. Case VIII: GJR(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	5.33	0.20	0.19	10.60	0.35	0.34	30.91	0.15	0.15
[0, 1]	6.76	0.25	0.24	29.14	0.96	0.94	169.08	0.82	0.81
[0, 2]	28.25	1.04	1.02	31.50	1.03	1.02	105.07	0.51	0.50
[0, 3]	−5.84	−0.21	−0.21	−21.72	−0.71	−0.70	175.61	0.85	0.83
[0, 4]	13.81	0.51	0.50	−71.68	−2.35	−2.31	122.01	0.59	0.58
[0, 5]	42.17	1.55	1.52	−0.97	−0.03	−0.03	36.60	0.18	0.17
[0, 6]	76.67	2.81	2.77	12.22	0.40	0.39	133.42	0.65	0.64
[0, 7]	99.43	3.65 *	3.58 *	49.18	1.61	1.59	273.75	1.33	1.30
[0, 8]	81.67	2.99 *	2.95 *	47.71	1.57	1.54	164.10	0.79	0.78
[0, 9]	84.83	3.11 *	3.06 *	48.14	1.58	1.55	300.80	1.46	1.43
[0, 10]	44.71	1.64	1.61	10.26	0.34	0.33	268.24	1.30	1.28
[0, 11]	62.13	2.28	2.24	6.14	0.20	0.20	127.48	0.62	0.61
[0, 12]	77.98	2.86	2.82	29.36	0.96	0.95	170.66	0.83	0.81
[0, 13]	97.87	3.59 *	3.53 *	26.29	0.86	0.85	280.62	1.36	1.34
[0, 14]	92.52	3.39 *	3.34 *	23.67	0.78	0.77	345.06	1.67	1.65
[0, 15]	119.40	4.38 **	4.31 **	51.71	1.70	1.67	274.56	1.33	1.31
[0, 16]	96.88	3.55 *	3.50 *	48.04	1.58	1.55	260.49	1.26	1.24
[0, 17]	22.45	0.82	0.81	−17.44	−0.57	−0.56	383.88	1.86	1.83
[0, 18]	109.36	4.01 *	3.95 *	62.23	2.04	2.01	354.31	1.72	1.69
[0, 19]	93.11	3.41 *	3.36 *	27.71	0.91	0.90	308.40	1.49	1.47
[0, 20]	86.87	3.19 *	3.14 *	45.68	1.50	1.48	197.47	0.96	0.94
[0, 21]	72.43	2.66	2.61	79.84	2.62	2.58	444.04	2.15	2.12
[0, 22]	58.59	2.15	2.12	99.49	3.26	3.22	453.87	2.20	2.16
[0, 23]	69.53	2.55	2.51	123.49	4.05 *	3.99 *	370.35	1.79	1.77
[0, 24]	53.44	1.96	1.93	114.06	3.74 *	3.68 *	418.25	2.03	1.99
[0, 25]	98.62	3.62 *	3.56 *	150.39	4.94 **	4.86 **	352.82	1.71	1.68
[0, 26]	78.95	2.89	2.85	191.53	6.29 **	6.19 **	318.31	1.54	1.52
[0, 27]	115.29	4.23 *	4.16 *	212.99	6.99 **	6.88 **	320.15	1.55	1.53
[0, 28]	96.74	3.55 *	3.49 *	187.86	6.16 **	6.07 **	287.17	1.39	1.37
[0, 29]	50.11	1.84	1.81	147.61	4.84 **	4.77 **	400.92	1.94	1.91
[0, 30]	45.06	1.65	1.62	82.95	2.72	2.68	238.27	1.15	1.13

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A32. Case VIII: EGARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period $[\tau_1, \tau_2]$	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	4.22	0.15	0.15	9.63	0.31	0.31	31.89	0.14	0.13
[0, 1]	5.42	0.19	0.19	27.20	0.88	0.87	171.50	0.73	0.72
[0, 2]	27.53	0.99	0.97	28.57	0.93	0.91	109.34	0.47	0.46
[0, 3]	−10.86	−0.39	−0.38	−25.57	−0.83	−0.81	179.26	0.77	0.75
[0, 4]	11.01	0.40	0.39	−76.54	−2.48	−2.44	128.32	0.55	0.54
[0, 5]	37.63	1.35	1.33	−6.78	−0.22	−0.22	43.58	0.19	0.18
[0, 6]	70.89	2.54	2.51	5.44	0.18	0.17	141.32	0.60	0.59
[0, 7]	93.21	3.35 *	3.29 *	41.43	1.34	1.32	282.97	1.21	1.19
[0, 8]	73.61	2.64	2.60	39.00	1.26	1.24	173.94	0.74	0.73
[0, 9]	76.39	2.74	2.70	38.46	1.25	1.23	311.99	1.33	1.31
[0, 10]	34.33	1.23	1.21	−0.37	−0.01	−0.01	280.00	1.20	1.18
[0, 11]	50.46	1.81	1.78	−5.45	−0.18	−0.17	140.13	0.60	0.59
[0, 12]	65.39	2.35	2.31	16.80	0.54	0.54	184.40	0.79	0.78
[0, 13]	84.20	3.02 *	2.98 *	12.76	0.41	0.41	295.36	1.26	1.24
[0, 14]	77.37	2.78	2.74	9.19	0.30	0.29	360.60	1.54	1.52
[0, 15]	104.36	3.75 *	3.69 *	36.24	1.17	1.16	291.70	1.25	1.23
[0, 16]	80.20	2.88	2.84	31.62	1.02	1.01	278.35	1.19	1.17
[0, 17]	3.26	0.12	0.11	−34.81	−1.13	−1.11	402.01	1.72	1.69
[0, 18]	90.32	3.24 *	3.19 *	43.88	1.42	1.40	374.06	1.60	1.57
[0, 19]	72.67	2.61	2.57	8.40	0.27	0.27	328.99	1.41	1.38
[0, 20]	66.04	2.37	2.33	25.40	0.82	0.81	219.41	0.94	0.92
[0, 21]	51.18	1.84	1.81	58.58	1.90	1.87	467.32	2.00	1.97
[0, 22]	35.14	1.26	1.24	77.28	2.50	2.47	477.58	2.04	2.01
[0, 23]	44.86	1.61	1.59	100.32	3.25 *	3.20 *	394.98	1.69	1.66
[0, 24]	27.18	0.98	0.96	89.93	2.91	2.87	443.63	1.90	1.87
[0, 25]	71.97	2.58	2.54	125.29	4.06 *	4.00 *	379.55	1.62	1.60
[0, 26]	50.80	1.82	1.80	165.47	5.36 **	5.28 **	345.83	1.48	1.46
[0, 27]	87.40	3.14 *	3.09 *	185.95	6.02 **	5.93 **	349.34	1.49	1.47
[0, 28]	67.93	2.44	2.40	159.85	5.18 **	5.10 **	317.45	1.36	1.34
[0, 29]	20.48	0.74	0.72	118.63	3.84 *	3.78 *	432.33	1.85	1.82
[0, 30]	12.26	0.44	0.43	53.03	1.72	1.69	269.62	1.15	1.13

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A33. Case IX: OLS—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	0.39	0.01	0.01	−12.89	−0.47	−0.46	−34.37	−0.42	−0.41
[0, 1]	−15.28	−0.56	−0.55	−26.34	−0.96	−0.95	−206.67	−2.51	−2.48
[0, 2]	−4.47	−0.16	−0.16	−25.11	−0.92	−0.90	−235.45	−2.86	−2.82
[0, 3]	3.48	0.13	0.12	−2.73	−0.10	−0.10	−75.79	−0.92	−0.91
[0, 4]	−13.91	−0.51	−0.50	−12.41	−0.45	−0.45	−68.70	−0.84	−0.82
[0, 5]	−7.10	−0.26	−0.25	−35.59	−1.30	−1.28	−154.55	−1.88	−1.85
[0, 6]	−16.97	−0.62	−0.60	−41.95	−1.53	−1.50	−103.91	−1.26	−1.23
[0, 7]	−26.45	−0.96	−0.95	−33.35	−1.22	−1.20	−131.33	−1.60	−1.57
[0, 8]	−65.79	−2.40	−2.35	−42.39	−1.55	−1.52	−145.12	−1.77	−1.73
[0, 9]	−62.43	−2.27	−2.23	−39.33	−1.44	−1.41	−94.88	−1.15	−1.13
[0, 10]	−59.72	−2.18	−2.13	−46.32	−1.69	−1.66	−149.71	−1.82	−1.78
[0, 11]	−61.38	−2.24	−2.13	−14.47	−0.53	−0.51	−30.49	−0.37	−0.35
[0, 12]	−46.84	−1.71	−1.67	2.17	0.08	0.08	60.71	0.74	0.72
[0, 13]	−52.86	−1.93	−1.89	4.84	0.18	0.17	55.12	0.67	0.66
[0, 14]	−59.78	−2.18	−2.02	−10.99	−0.40	−0.37	−176.64	−2.15	−2.00
[0, 15]	−25.70	−0.94	−0.92	46.52	1.70	1.68	−242.71	−2.95 *	−2.91
[0, 16]	6.29	0.23	0.22	58.06	2.12	2.05	−113.18	−1.38	−1.33
[0, 17]	−9.88	−0.36	−0.35	23.93	0.88	0.85	−73.47	−0.89	−0.87
[0, 18]	−35.13	−1.28	−1.26	3.26	0.12	0.12	23.43	0.28	0.28
[0, 19]	−37.25	−1.36	−1.34	−42.08	−1.54	−1.52	−1.48	−0.02	−0.02
[0, 20]	−22.02	−0.80	−0.76	−57.13	−2.09	−1.97	−93.89	−1.14	−1.08
[0, 21]	−17.07	−0.62	−0.60	−79.14	−2.90	−2.79	−108.85	−1.32	−1.27
[0, 22]	−38.23	−1.39	−1.37	−99.91	−3.66 *	−3.60 *	−155.53	−1.89	−1.86
[0, 23]	−49.72	−1.81	−1.78	−110.71	−4.05 *	−3.98 *	−288.68	−3.51 *	−3.45 *
[0, 24]	−57.53	−2.10	−2.06	−133.39	−4.88 **	−4.80 **	−33.24	−0.40	−0.40
[0, 25]	−108.41	−3.95 *	−3.88 *	−133.59	−4.89 **	−4.80 **	−213.51	−2.60	−2.55
[0, 26]	−111.51	−4.06 *	−3.96 *	−171.75	−6.28 **	−6.12 **	−195.14	−2.37	−2.31
[0, 27]	−132.55	−4.83 **	−4.67 **	−185.87	−6.80 **	−6.58 **	−367.89	−4.47 **	−4.33 *
[0, 28]	−128.69	−4.69 **	−4.61 **	−161.39	−5.91 **	−5.80 **	−341.62	−4.16 *	−4.08 *
[0, 29]	−164.70	−6.00 **	−5.90 **	−187.69	−6.87 **	−6.75 **	−290.17	−3.53 *	−3.47 *
[0, 30]	−108.27	−3.94 *	−3.88 *	−129.58	−4.74 **	−4.67 **	−281.02	−3.42 *	−3.37 *

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A34. Case IX: GARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	0.02	0.00	0.00	−11.31	−0.38	−0.37	−26.86	−0.34	−0.33
[0, 1]	−15.22	−0.71	−0.70	−24.82	−0.83	−0.82	−195.94	−2.47	−2.43
[0, 2]	−3.98	−0.19	−0.18	−23.66	−0.79	−0.78	−221.55	−2.79	−2.75
[0, 3]	4.34	0.20	0.20	−1.21	−0.04	−0.04	−58.36	−0.73	−0.72
[0, 4]	−12.89	−0.60	−0.59	−10.40	−0.35	−0.34	−46.62	−0.59	−0.58
[0, 5]	−5.53	−0.26	−0.25	−33.89	−1.13	−1.12	−129.97	−1.64	−1.61
[0, 6]	−14.29	−0.67	−0.65	−41.71	−1.39	−1.36	−79.83	−1.01	−0.98
[0, 7]	−23.82	−1.11	−1.09	−32.19	−1.08	−1.06	−101.45	−1.28	−1.25
[0, 8]	−62.27	−2.91	−2.86	−42.21	−1.41	−1.38	−114.51	−1.44	−1.41
[0, 9]	−58.93	−2.76	−2.71	−38.30	−1.28	−1.26	−58.65	−0.74	−0.73
[0, 10]	−56.45	−2.64	−2.58	−43.99	−1.47	−1.44	−106.69	−1.34	−1.31
[0, 11]	−56.42	−2.64	−2.52	−14.79	−0.49	−0.47	8.86	0.11	0.11
[0, 12]	−40.88	−1.91	−1.87	0.61	0.02	0.02	100.12	1.26	1.23
[0, 13]	−47.09	−2.20	−2.16	4.49	0.15	0.15	101.09	1.27	1.25
[0, 14]	−55.45	−2.59	−2.41	−7.55	−0.25	−0.23	−117.28	−1.48	−1.37
[0, 15]	−21.11	−0.99	−0.97	50.24	1.68	1.65	−179.26	−2.26	−2.22
[0, 16]	12.25	0.57	0.55	59.80	2.00	1.93	−51.64	−0.65	−0.63
[0, 17]	−2.74	−0.13	−0.12	24.06	0.80	0.78	−12.84	−0.16	−0.16
[0, 18]	−27.24	−1.27	−1.25	2.67	0.09	0.09	85.52	1.08	1.06
[0, 19]	−29.02	−1.36	−1.34	−42.55	−1.42	−1.40	64.25	0.81	0.80
[0, 20]	−14.95	−0.70	−0.66	−54.39	−1.82	−1.72	−16.30	−0.21	−0.19
[0, 21]	−10.75	−0.50	−0.48	−74.03	−2.47	−2.38	−21.63	−0.27	−0.26
[0, 22]	−31.41	−1.47	−1.45	−95.00	−3.18 *	−3.13 *	−65.49	−0.82	−0.81
[0, 23]	−42.12	−1.97	−1.93	−106.61	−3.56 *	−3.50 *	−197.43	−2.49	−2.44
[0, 24]	−49.19	−2.30	−2.26	−129.98	−4.34 *	−4.27 *	59.54	0.75	0.74
[0, 25]	−100.14	−4.68 **	−4.60 **	−129.22	−4.32 *	−4.24 *	−114.83	−1.45	−1.42
[0, 26]	−103.62	−4.85 **	−4.72 **	−165.76	−5.54 **	−5.40 **	−88.83	−1.12	−1.09
[0, 27]	−125.27	−5.86 **	−5.67 **	−177.79	−5.94 **	−5.75 **	−252.71	−3.18 *	−3.08 *
[0, 28]	−121.38	−5.68 **	−5.58 **	−152.56	−5.10 **	−5.01 **	−221.10	−2.78	−2.74
[0, 29]	−156.69	−7.33 **	−7.20 **	−179.50	−6.00 **	−5.90 **	−167.97	−2.12	−2.08
[0, 30]	−99.98	−4.68 **	−4.61 **	−121.12	−4.05 *	−3.99 *	−154.76	−1.95	−1.92

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A35. Case IX: GJR(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	0.52	0.03	0.03	−11.51	−0.35	−0.34	−6.10	−0.02	−0.02
[0, 1]	−14.44	−0.74	−0.73	−25.22	−0.76	−0.75	−165.91	−0.48	−0.47
[0, 2]	−2.92	−0.15	−0.15	−24.26	−0.73	−0.72	−182.40	−0.53	−0.52
[0, 3]	5.69	0.29	0.29	−2.02	−0.06	−0.06	−9.13	−0.03	−0.03
[0, 4]	−11.19	−0.57	−0.56	−11.41	−0.34	−0.34	15.71	0.05	0.04
[0, 5]	−3.57	−0.18	−0.18	−35.11	−1.05	−1.04	−60.29	−0.17	−0.17
[0, 6]	−12.24	−0.63	−0.61	−43.14	−1.29	−1.26	−10.90	−0.03	−0.03
[0, 7]	−21.36	−1.10	−1.08	−33.82	−1.01	−1.00	−16.36	−0.05	−0.05
[0, 8]	−59.66	−3.06 *	−3.00 *	−44.06	−1.32	−1.30	−26.81	−0.08	−0.08
[0, 9]	−55.92	−2.87	−2.82	−40.34	−1.21	−1.19	44.74	0.13	0.13
[0, 10]	−52.98	−2.72	−2.66	−46.22	−1.39	−1.36	15.54	0.05	0.04
[0, 11]	−53.01	−2.72	−2.59	−17.26	−0.52	−0.49	121.83	0.35	0.34
[0, 12]	−37.35	−1.92	−1.87	−2.08	−0.06	−0.06	213.90	0.62	0.61
[0, 13]	−43.11	−2.21	−2.17	1.61	0.05	0.05	233.08	0.68	0.66
[0, 14]	−50.68	−2.60	−2.42	−10.61	−0.32	−0.30	51.23	0.15	0.14
[0, 15]	−16.01	−0.82	−0.81	46.99	1.41	1.39	0.87	0.00	0.00
[0, 16]	17.37	0.89	0.86	56.32	1.69	1.63	123.97	0.36	0.35
[0, 17]	2.46	0.13	0.12	20.36	0.61	0.59	160.94	0.47	0.45
[0, 18]	−21.86	−1.12	−1.10	−1.23	−0.04	−0.04	263.85	0.77	0.75
[0, 19]	−23.33	−1.20	−1.18	−46.67	−1.40	−1.38	252.98	0.73	0.72
[0, 20]	−8.54	−0.44	−0.41	−58.68	−1.76	−1.66	204.86	0.59	0.56
[0, 21]	−3.74	−0.19	−0.18	−78.51	−2.36	−2.27	225.97	0.66	0.63
[0, 22]	−24.14	−1.24	−1.22	−99.68	−2.99 *	−2.94 *	190.29	0.55	0.54
[0, 23]	−34.66	−1.78	−1.75	−111.51	−3.35 *	−3.28 *	62.21	0.18	0.18
[0, 24]	−41.54	−2.13	−2.09	−135.08	−4.05 *	−3.98 *	323.90	0.94	0.92
[0, 25]	−92.08	−4.72 **	−4.64 **	−134.52	−4.04 *	−3.96 *	166.00	0.48	0.47
[0, 26]	−95.05	−4.88 **	−4.75 **	−171.26	−5.14 **	−5.01 **	213.08	0.62	0.60
[0, 27]	−116.14	−5.96 **	−5.76 **	−183.47	−5.51 **	−5.33 **	73.60	0.21	0.21
[0, 28]	−111.86	−5.74 **	−5.64 **	−158.44	−4.75 **	−4.67 **	120.17	0.35	0.34
[0, 29]	−146.96	−7.54 **	−7.41 **	−185.59	−5.57 **	−5.47 **	178.42	0.52	0.51
[0, 30]	−89.93	−4.61 **	−4.54 **	−127.41	−3.82 *	−3.76 *	203.13	0.59	0.58

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A36. Case IX: EGARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	−2.24	−0.05	−0.05	−11.21	−0.35	−0.34	−2.21	−0.01	−0.01
[0, 1]	−18.52	−0.41	−0.40	−24.90	−0.77	−0.76	−159.93	−0.39	−0.39
[0, 2]	−8.30	−0.18	−0.18	−23.93	−0.74	−0.73	−174.35	−0.43	−0.42
[0, 3]	−1.10	−0.02	−0.02	−1.65	−0.05	−0.05	1.13	0.00	0.00
[0, 4]	−19.78	−0.43	−0.43	−10.93	−0.34	−0.33	28.66	0.07	0.07
[0, 5]	−13.24	−0.29	−0.29	−34.66	−1.07	−1.05	−45.55	−0.11	−0.11
[0, 6]	−21.96	−0.48	−0.47	−42.92	−1.32	−1.29	4.36	0.01	0.01
[0, 7]	−33.27	−0.73	−0.72	−33.41	−1.03	−1.01	2.08	0.01	0.01
[0, 8]	−72.04	−1.58	−1.55	−43.79	−1.35	−1.32	−7.33	−0.02	−0.02
[0, 9]	−70.42	−1.55	−1.52	−39.90	−1.23	−1.21	67.32	0.17	0.16
[0, 10]	−70.01	−1.54	−1.50	−45.54	−1.40	−1.37	41.71	0.10	0.10
[0, 11]	−69.02	−1.52	−1.45	−16.99	−0.52	−0.50	147.19	0.36	0.34
[0, 12]	−53.61	−1.18	−1.15	−2.00	−0.06	−0.06	240.02	0.59	0.58
[0, 13]	−61.81	−1.36	−1.33	1.92	0.06	0.06	262.69	0.64	0.63
[0, 14]	−74.13	−1.63	−1.51	−9.62	−0.30	−0.28	87.19	0.21	0.20
[0, 15]	−41.07	−0.90	−0.89	48.05	1.48	1.46	39.30	0.10	0.09
[0, 16]	−7.27	−0.16	−0.15	57.07	1.76	1.70	162.33	0.40	0.38
[0, 17]	−22.11	−0.49	−0.47	20.86	0.64	0.62	199.65	0.49	0.48
[0, 18]	−47.14	−1.04	−1.02	−0.83	−0.03	−0.03	303.91	0.75	0.73
[0, 19]	−50.07	−1.10	−1.08	−46.22	−1.42	−1.40	295.31	0.72	0.71
[0, 20]	−39.52	−0.87	−0.82	−57.66	−1.78	−1.68	252.91	0.62	0.59
[0, 21]	−38.20	−0.84	−0.81	−77.05	−2.37	−2.28	278.79	0.68	0.66
[0, 22]	−59.78	−1.31	−1.29	−98.24	−3.02 *	−2.98 *	245.04	0.60	0.59
[0, 23]	−70.93	−1.56	−1.53	−110.17	−3.39 *	−3.33 *	118.20	0.29	0.28
[0, 24]	−78.56	−1.73	−1.70	−133.84	−4.12 *	−4.05 *	381.27	0.93	0.92
[0, 25]	−131.31	−2.88	−2.83	−133.08	−4.10 *	−4.02 *	226.58	0.56	0.55
[0, 26]	−137.09	−3.01 *	−2.93 *	−169.52	−5.22 **	−5.09 **	277.60	0.68	0.66
[0, 27]	−161.40	−3.55 *	−3.43 *	−181.35	−5.58 **	−5.40 **	142.57	0.35	0.34
[0, 28]	−159.15	−3.50 *	−3.44 *	−156.17	−4.81 **	−4.73 *	192.13	0.47	0.46
[0, 29]	−195.05	−4.28 *	−4.21 *	−183.39	−5.65 **	−5.55 **	251.82	0.62	0.61
[0, 30]	−139.62	−3.07 *	−3.02 *	−125.14	−3.85 *	−3.79 *	278.97	0.68	0.67

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A37. Case X: OLS—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	18.83	0.54	0.53	−13.96	−0.49	−0.49	10.03	0.15	0.15
[0, 1]	3.86	0.11	0.11	12.71	0.45	0.44	9.46	0.14	0.14
[0, 2]	56.09	1.61	1.57	74.82	2.65	2.59	−108.42	−1.64	−1.61
[0, 3]	75.46	2.16	2.12	67.11	2.38	2.33	12.35	0.19	0.18
[0, 4]	80.23	2.30	2.26	49.13	1.74	1.71	20.73	0.31	0.31
[0, 5]	47.51	1.36	1.34	16.40	0.58	0.57	37.70	0.57	0.56
[0, 6]	47.67	1.37	1.33	9.08	0.32	0.31	3.11	0.05	0.05
[0, 7]	70.01	2.01	1.95	−20.97	−0.74	−0.72	11.20	0.17	0.16
[0, 8]	43.58	1.25	1.22	−59.91	−2.12	−2.07	−80.58	−1.22	−1.19
[0, 9]	63.34	1.81	1.79	−39.46	−1.40	−1.37	10.01	0.15	0.15
[0, 10]	60.68	1.74	1.70	−63.20	−2.24	−2.19	−36.33	−0.55	−0.54
[0, 11]	59.42	1.70	1.66	−95.49	−3.38 *	−3.29 *	−119.72	−1.81	−1.76
[0, 12]	29.16	0.84	0.81	−126.85	−4.49 **	−4.34 **	−46.99	−0.71	−0.69
[0, 13]	19.27	0.55	0.54	−122.76	−4.35 *	−4.21 *	−108.72	−1.64	−1.59
[0, 14]	27.11	0.78	0.75	−118.11	−4.18*	−4.06 *	−164.76	−2.49	−2.42
[0, 15]	−5.40	−0.15	−0.15	−153.50	−5.43 **	−5.26 **	−227.77	−3.44 *	−3.33 *
[0, 16]	12.31	0.35	0.34	−188.65	−6.68 **	−6.46 **	−287.11	−4.34 **	−4.20 **
[0, 17]	19.17	0.55	0.54	−131.37	−4.65 **	−4.55 **	−272.49	−4.12 *	−4.03 *
[0, 18]	39.32	1.13	1.10	−134.67	−4.77 **	−4.66 **	−116.81	−1.77	−1.73
[0, 19]	19.16	0.55	0.53	−147.38	−5.22 **	−5.06 **	−172.01	−2.60	−2.52
[0, 20]	20.69	0.59	0.58	−156.30	−5.53 **	−5.40 **	−188.53	−2.85	−2.78
[0, 21]	34.44	0.99	0.96	−149.10	−5.28 **	−5.13 **	−87.51	−1.32	−1.29
[0, 22]	26.75	0.77	0.75	−150.47	−5.33 **	−5.24 **	−87.63	−1.32	−1.30
[0, 23]	23.29	0.67	0.66	−155.27	−5.50 **	−5.41 **	−77.14	−1.17	−1.15
[0, 24]	20.42	0.58	0.57	−134.70	−4.77 **	−4.66 **	−49.66	−0.75	−0.73
[0, 25]	41.49	1.19	1.16	−130.28	−4.61 **	−4.51 **	−106.32	−1.61	−1.57
[0, 26]	20.13	0.58	0.56	−153.79	−5.44 **	−5.32 **	−32.29	−0.49	−0.48
[0, 27]	30.01	0.86	0.84	−137.81	−4.88 **	−4.77 **	−35.92	−0.54	−0.53
[0, 28]	56.25	1.61	1.58	−125.99	−4.46 **	−4.37 **	−174.26	−2.63	−2.58
[0, 29]	28.02	0.80	0.78	−156.93	−5.56 **	−5.43 **	−84.12	−1.27	−1.24
[0, 30]	56.56	1.62	1.58	−166.06	−5.88 **	−5.75 **	−85.31	−1.29	−1.26

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A38. Case X: GARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	**Group-Type**			**Individual-Type**			**Medical-Type**		
	CAR	**t-Value**		**CAR**	**t-Value**		**CAR**	**t-Value**	
		TM	**SRM**		**TM**	**SRM**		**TM**	**SRM**
[0, 0]	23.11	0.55	0.55	−13.33	−0.34	−0.34	29.21	0.35	0.35
[0, 1]	7.16	0.17	0.17	12.21	0.32	0.31	23.92	0.29	0.29
[0, 2]	56.87	1.37	1.34	72.68	1.88	1.84	−105.60	−1.28	−1.25
[0, 3]	77.66	1.86	1.83	64.64	1.67	1.64	21.33	0.26	0.25
[0, 4]	82.66	1.98	1.95	45.95	1.19	1.17	30.55	0.37	0.36
[0, 5]	51.49	1.24	1.22	12.93	0.33	0.33	54.28	0.66	0.65
[0, 6]	49.00	1.18	1.15	3.93	0.10	0.10	7.45	0.09	0.09
[0, 7]	71.57	1.72	1.67	−26.84	−0.69	−0.68	16.31	0.20	0.19
[0, 8]	45.93	1.10	1.07	−66.32	−1.72	−1.67	−72.10	−0.87	−0.85
[0, 9]	70.78	1.70	1.67	−44.97	−1.16	−1.15	41.31	0.50	0.49
[0, 10]	70.56	1.69	1.66	−68.70	−1.78	−1.74	5.74	0.07	0.07
[0, 11]	70.86	1.70	1.66	−101.27	−2.62	−2.55	−70.82	−0.86	−0.83
[0, 12]	41.96	1.01	0.97	−132.97	−3.44 *	−3.33 *	7.84	0.09	0.09
[0, 13]	32.23	0.77	0.75	−129.63	−3.35 *	−3.25 *	−53.42	−0.65	−0.63
[0, 14]	40.36	0.97	0.94	−125.69	−3.25 *	−3.16 *	−108.39	−1.31	−1.27
[0, 15]	8.74	0.21	0.20	−161.58	−4.18 *	−4.04 *	−167.57	−2.03	−1.96
[0, 16]	26.84	0.64	0.62	−197.40	−5.11 **	−4.94 **	−225.40	−2.73	−2.64
[0, 17]	32.43	0.78	0.76	−141.33	−3.66 *	−3.58 *	−216.77	−2.62	−2.57
[0, 18]	53.02	1.27	1.24	−145.29	−3.76 *	−3.68 *	−59.33	−0.72	−0.70
[0, 19]	34.71	0.83	0.81	−158.19	−4.09 *	−3.97 *	−106.43	−1.29	−1.25
[0, 20]	35.62	0.86	0.83	−168.10	−4.35 **	−4.25 *	−125.97	−1.53	−1.49
[0, 21]	50.58	1.21	1.18	−161.31	−4.17 *	−4.06 *	−19.69	−0.24	−0.23
[0, 22]	40.64	0.98	0.96	−164.22	−4.25 **	−4.18 *	−30.26	−0.37	−0.36
[0, 23]	36.63	0.88	0.87	−170.01	−4.40 **	−4.33 **	−22.53	−0.27	−0.27
[0, 24]	37.17	0.89	0.87	−149.10	−3.86 *	−3.77 *	20.16	0.24	0.24
[0, 25]	58.13	1.40	1.37	−145.52	−3.76 *	−3.69 *	−37.23	−0.45	−0.44
[0, 26]	37.66	0.90	0.88	−169.53	−4.39 **	−4.29 **	40.60	0.49	0.48
[0, 27]	47.78	1.15	1.12	−154.26	−3.99 *	−3.90 *	37.79	0.46	0.45
[0, 28]	74.20	1.78	1.74	−143.19	−3.70 *	−3.63 *	−99.94	−1.21	−1.19
[0, 29]	46.88	1.13	1.10	−174.63	−4.52 **	−4.42 **	−5.96	−0.07	−0.07
[0, 30]	75.67	1.82	1.78	−184.47	−4.77 **	−4.67 **	−6.27	−0.08	−0.07

Note: ** and * denote significance at the 5% and 10% levels, respectively.

Table A39. Case X: GJR(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	7.00	0.10	0.10	−10.96	−0.17	−0.17	28.74	0.42	0.42
[0, 1]	−7.33	−0.10	−0.10	12.33	0.20	0.19	22.21	0.33	0.32
[0, 2]	49.14	0.69	0.68	69.21	1.10	1.08	−108.78	−1.61	−1.57
[0, 3]	63.49	0.89	0.88	61.03	0.97	0.95	17.27	0.26	0.25
[0, 4]	65.98	0.93	0.91	41.15	0.65	0.64	25.43	0.38	0.37
[0, 5]	27.92	0.39	0.39	8.11	0.13	0.13	48.30	0.71	0.70
[0, 6]	32.64	0.46	0.45	−4.60	−0.07	−0.07	−0.02	0.00	0.00
[0, 7]	52.75	0.74	0.72	−36.56	−0.58	−0.56	7.77	0.11	0.11
[0, 8]	22.74	0.32	0.31	−76.73	−1.22	−1.19	−81.62	−1.21	−1.17
[0, 9]	28.77	0.41	0.40	−52.30	−0.83	−0.82	31.45	0.46	0.46
[0, 10]	18.68	0.26	0.26	−75.29	−1.19	−1.17	−4.86	−0.07	−0.07
[0, 11]	12.02	0.17	0.16	−107.87	−1.71	−1.67	−82.28	−1.22	−1.18
[0, 12]	−23.15	−0.33	−0.32	−139.77	−2.22	−2.15	−4.52	−0.07	−0.06
[0, 13]	−35.11	−0.49	−0.48	−137.67	−2.18	−2.12	−66.86	−0.99	−0.96
[0, 14]	−29.65	−0.42	−0.41	−134.86	−2.14	−2.08	−122.88	−1.82	−1.76
[0, 15]	−65.99	−0.93	−0.90	−171.35	−2.72	−2.63	−183.02	−2.70	−2.62
[0, 16]	−50.89	−0.72	−0.69	−208.22	−3.30 *	−3.20 *	−241.89	−3.57 *	−3.46 *
[0, 17]	−42.73	−0.60	−0.59	−154.65	−2.45	−2.40	−234.54	−3.47 *	−3.39 *
[0, 18]	−25.33	−0.36	−0.35	−159.60	−2.53	−2.48	−78.13	−1.15	−1.13
[0, 19]	−51.52	−0.73	−0.70	−172.27	−2.73	−2.65	−126.06	−1.86	−1.81
[0, 20]	−50.25	−0.71	−0.69	−184.11	−2.92 *	−2.85	−146.78	−2.17	−2.12
[0, 21]	−41.07	−0.58	−0.56	−177.64	−2.82	−2.74	−41.42	−0.61	−0.59
[0, 22]	−45.13	−0.64	−0.63	−183.92	−2.92	−2.87	−53.42	−0.79	−0.78
[0, 23]	−48.97	−0.69	−0.68	−191.57	−3.04 *	−2.99 *	−46.86	−0.69	−0.68
[0, 24]	−61.61	−0.87	−0.85	−169.06	−2.68	−2.62	−4.76	−0.07	−0.07
[0, 25]	−41.98	−0.59	−0.58	−166.95	−2.65	−2.59	−63.26	−0.93	−0.92
[0, 26]	−67.14	−0.95	−0.92	−191.57	−3.04 *	−2.97 *	13.60	0.20	0.20
[0, 27]	−59.52	−0.84	−0.82	−177.49	−2.82	−2.75	9.73	0.14	0.14
[0, 28]	−35.41	−0.50	−0.49	−167.63	−2.66	−2.61	−129.07	−1.91	−1.87
[0, 29]	−67.47	−0.95	−0.93	−199.67	−3.17 *	−3.10 *	−36.05	−0.53	−0.52
[0, 30]	−41.21	−0.58	−0.57	−210.68	−3.34 *	−3.27 *	−37.42	−0.55	−0.54

Note: * denotes significance at the 10% level.

Table A40. Case X: EGARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	12.98	0.29	0.28	−15.89	−0.16	−0.15	19.29	0.11	0.11
[0, 1]	−2.07	−0.05	−0.05	7.31	0.07	0.07	22.72	0.13	0.13
[0, 2]	51.73	1.15	1.13	65.49	0.65	0.63	−92.69	−0.54	−0.53
[0, 3]	68.40	1.52	1.49	55.01	0.54	0.53	34.48	0.20	0.20
[0, 4]	71.74	1.59	1.57	33.91	0.33	0.33	48.08	0.28	0.27
[0, 5]	36.17	0.80	0.79	−1.55	−0.02	−0.02	71.58	0.41	0.41
[0, 6]	38.06	0.85	0.82	−12.83	−0.13	−0.12	39.33	0.23	0.22
[0, 7]	58.99	1.31	1.27	−46.00	−0.45	−0.44	52.62	0.30	0.30
[0, 8]	30.52	0.68	0.66	−87.90	−0.87	−0.84	−33.37	−0.19	−0.19
[0, 9]	43.55	0.97	0.95	−69.14	−0.68	−0.67	67.27	0.39	0.38
[0, 10]	37.07	0.82	0.81	−95.35	−0.94	−0.92	28.34	0.16	0.16
[0, 11]	32.94	0.73	0.71	−130.37	−1.29	−1.25	−48.51	−0.28	−0.27
[0, 12]	0.02	0.00	0.00	−164.51	−1.62	−1.57	30.56	0.18	0.17
[0, 13]	−11.20	−0.25	−0.24	−163.56	−1.61	−1.56	−26.03	−0.15	−0.15
[0, 14]	−4.84	−0.11	−0.10	−162.02	−1.60	−1.55	−76.79	−0.44	−0.43
[0, 15]	−39.50	−0.88	−0.85	−200.33	−1.98	−1.91	−133.92	−0.77	−0.75
[0, 16]	−23.38	−0.52	−0.50	−238.55	−2.35	−2.28	−187.90	−1.09	−1.05
[0, 17]	−16.30	−0.36	−0.35	−184.82	−1.82	−1.78	−169.56	−0.98	−0.96
[0, 18]	2.20	0.05	0.05	−191.18	−1.89	−1.84	−8.45	−0.05	−0.05
[0, 19]	−21.13	−0.47	−0.46	−206.54	−2.04	−1.98	−56.83	−0.33	−0.32
[0, 20]	−20.11	−0.45	−0.44	−218.82	−2.16	−2.11	−68.98	−0.40	−0.39
[0, 21]	−8.85	−0.20	−0.19	−214.46	−2.12	−2.06	38.24	0.22	0.22
[0, 22]	−15.24	−0.34	−0.33	−219.67	−2.17	−2.13	40.86	0.24	0.23
[0, 23]	−19.26	−0.43	−0.42	−227.83	−2.25	−2.21	55.78	0.32	0.32
[0, 24]	−27.02	−0.60	−0.59	−209.43	−2.07	−2.02	91.64	0.53	0.52
[0, 25]	−7.00	−0.16	−0.15	−208.23	−2.05	−2.01	39.86	0.23	0.23
[0, 26]	−30.50	−0.68	−0.66	−234.67	−2.32	−2.26	119.76	0.69	0.68
[0, 27]	−22.04	−0.49	−0.48	−221.80	−2.19	−2.14	121.35	0.70	0.69
[0, 28]	2.83	0.06	0.06	−213.12	−2.10	−2.06	−11.82	−0.07	−0.07
[0, 29]	−27.55	−0.61	−0.60	−246.98	−2.44	−2.38	84.20	0.49	0.48
[0, 30]	−0.44	−0.01	−0.01	−259.23	−2.56	−2.50	88.25	0.51	0.50

Table A41. Case XI: OLS—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period $[\tau_1, \tau_2]$	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	−15.18	−0.65	−0.64	37.05	1.66	1.63	−38.37	−0.40	−0.39
[0, 1]	−25.75	−1.11	−1.09	28.73	1.28	1.26	−76.77	−0.79	−0.78
[0, 2]	−16.16	−0.70	−0.68	15.61	0.70	0.69	−65.08	−0.67	−0.66
[0, 3]	−21.25	−0.91	−0.90	−5.39	−0.24	−0.24	−10.93	−0.11	−0.11
[0, 4]	−5.59	−0.24	−0.24	12.96	0.58	0.57	91.70	0.95	0.93
[0, 5]	2.68	0.12	0.11	8.99	0.40	0.40	−24.27	−0.25	−0.25
[0, 6]	−35.12	−1.51	−1.48	2.74	0.12	0.12	8.42	0.09	0.09
[0, 7]	−47.73	−2.05	−1.97	−43.28	−1.94	−1.85	48.04	0.50	0.47
[0, 8]	22.10	0.95	0.93	63.05	2.82	2.76	217.40	2.24	2.20
[0, 9]	9.98	0.43	0.42	36.07	1.61	1.59	123.78	1.28	1.26
[0, 10]	−11.06	−0.48	−0.47	29.23	1.31	1.29	60.51	0.62	0.61
[0, 11]	12.52	0.54	0.53	33.31	1.49	1.47	14.20	0.15	0.14
[0, 12]	15.91	0.68	0.67	29.51	1.32	1.30	−43.43	−0.45	−0.44
[0, 13]	−13.19	−0.57	−0.56	15.65	0.70	0.69	−10.34	−0.11	−0.11
[0, 14]	1.13	0.05	0.05	51.29	2.29	2.25	1.27	0.01	0.01
[0, 15]	1.18	0.05	0.05	35.71	1.60	1.56	−62.95	−0.65	−0.63
[0, 16]	22.49	0.97	0.95	26.35	1.18	1.16	151.59	1.56	1.54
[0, 17]	9.23	0.40	0.39	24.21	1.08	1.07	93.86	0.97	0.95
[0, 18]	14.84	0.64	0.63	32.07	1.43	1.41	36.54	0.38	0.37
[0, 19]	22.60	0.97	0.96	25.33	1.13	1.12	121.02	1.25	1.23
[0, 20]	6.75	0.29	0.29	18.06	0.81	0.79	−40.94	−0.42	−0.42
[0, 21]	12.30	0.53	0.52	42.30	1.89	1.86	42.88	0.44	0.44
[0, 22]	8.82	0.38	0.37	43.77	1.96	1.93	177.69	1.83	1.80
[0, 23]	12.65	0.54	0.54	24.49	1.09	1.08	20.75	0.21	0.21
[0, 24]	7.81	0.34	0.33	12.43	0.56	0.55	53.90	0.56	0.55
[0, 25]	5.87	0.25	0.25	9.74	0.44	0.43	150.81	1.56	1.53
[0, 26]	11.97	0.52	0.51	4.52	0.20	0.20	175.23	1.81	1.78
[0, 27]	−11.84	−0.51	−0.50	9.38	0.42	0.41	58.07	0.60	0.59
[0, 28]	8.80	0.38	0.37	27.92	1.25	1.23	37.34	0.39	0.38
[0, 29]	−1.65	−0.07	−0.07	31.26	1.40	1.37	186.99	1.93	1.89
[0, 30]	6.98	0.30	0.29	18.47	0.83	0.80	35.78	0.37	0.36

Table A42. Case XI: GARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	−15.10	−0.82	−0.68	36.24	1.18	1.16	−41.43	−0.38	−0.38
[0, 1]	−25.42	−1.39	−1.14	27.41	0.89	0.87	−83.77	−0.78	−0.76
[0, 2]	−15.62	−0.85	−0.70	13.71	0.45	0.44	−75.86	−0.70	−0.69
[0, 3]	−20.56	−1.12	−0.92	−7.95	−0.26	−0.25	−25.20	−0.23	−0.23
[0, 4]	−5.03	−0.27	−0.23	9.22	0.30	0.29	75.49	0.70	0.69
[0, 5]	3.54	0.19	0.16	4.83	0.16	0.15	−44.73	−0.41	−0.41
[0, 6]	−35.04	−1.91	−1.56	−3.67	−0.12	−0.12	−10.70	−0.10	−0.10
[0, 7]	−48.38	−2.64	−2.11	−51.86	−1.68	−1.61	30.01	0.28	0.27
[0, 8]	24.15	1.32	1.08	58.11	1.89	1.85	182.77	1.69	1.66
[0, 9]	11.70	0.64	0.53	29.62	0.96	0.95	88.23	0.82	0.80
[0, 10]	−8.89	−0.49	−0.40	22.60	0.73	0.72	19.96	0.18	0.18
[0, 11]	14.36	0.78	0.64	25.19	0.82	0.81	−27.34	−0.25	−0.25
[0, 12]	17.96	0.98	0.81	20.82	0.68	0.67	−88.73	−0.82	−0.81
[0, 13]	−10.42	−0.57	−0.47	7.22	0.23	0.23	−61.98	−0.57	−0.57
[0, 14]	4.55	0.25	0.20	43.03	1.40	1.37	−56.38	−0.52	−0.51
[0, 15]	5.10	0.28	0.23	27.36	0.89	0.87	−125.86	−1.17	−1.14
[0, 16]	25.86	1.41	1.16	16.13	0.52	0.52	88.88	0.82	0.81
[0, 17]	12.64	0.69	0.57	13.14	0.43	0.42	28.23	0.26	0.26
[0, 18]	18.02	0.98	0.81	19.65	0.64	0.63	−30.55	−0.28	−0.28
[0, 19]	26.30	1.44	1.18	12.88	0.42	0.41	48.52	0.45	0.44
[0, 20]	11.03	0.60	0.50	5.65	0.18	0.18	−119.08	−1.10	−1.09
[0, 21]	16.89	0.92	0.76	29.47	0.96	0.94	−39.51	−0.37	−0.36
[0, 22]	13.52	0.74	0.61	30.19	0.98	0.97	92.06	0.85	0.84
[0, 23]	17.47	0.95	0.78	10.17	0.33	0.33	−68.14	−0.63	−0.62
[0, 24]	12.97	0.71	0.58	−2.25	−0.07	−0.07	−39.42	−0.37	−0.36
[0, 25]	10.89	0.59	0.49	−6.10	−0.20	−0.20	55.50	0.51	0.51
[0, 26]	17.48	0.95	0.78	−11.45	−0.37	−0.37	74.80	0.69	0.68
[0, 27]	−5.72	−0.31	−0.26	−6.49	−0.21	−0.21	−48.20	−0.45	−0.44
[0, 28]	15.12	0.83	0.68	11.46	0.37	0.37	−72.64	−0.67	−0.66
[0, 29]	4.98	0.27	0.22	14.39	0.47	0.46	72.72	0.67	0.66
[0, 30]	13.61	0.74	0.60	0.65	0.02	0.02	−81.10	−0.75	−0.73

Table A43. Case XI: GJR (1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	−16.17	−0.37	−0.36	35.63	0.63	0.62	−26.36	−0.07	−0.07
[0, 1]	−27.80	−0.63	−0.62	25.65	0.45	0.45	−53.46	−0.14	−0.14
[0, 2]	−19.26	−0.44	−0.43	10.92	0.19	0.19	−30.33	−0.08	−0.08
[0, 3]	−25.38	−0.58	−0.57	−11.62	−0.21	−0.20	35.49	0.09	0.09
[0, 4]	−10.64	−0.24	−0.24	5.61	0.10	0.10	151.04	0.39	0.39
[0, 5]	−3.45	−0.08	−0.08	−0.10	0.00	0.00	46.12	0.12	0.12
[0, 6]	−41.93	−0.95	−0.93	−6.56	−0.12	−0.11	94.38	0.24	0.24
[0, 7]	−55.24	−1.26	−1.20	−52.87	−0.93	−0.89	149.37	0.39	0.37
[0, 8]	12.62	0.29	0.28	48.33	0.85	0.84	319.80	0.83	0.81
[0, 9]	−0.34	−0.01	−0.01	20.52	0.36	0.36	239.92	0.62	0.61
[0, 10]	−22.51	−0.51	−0.50	11.72	0.21	0.20	187.10	0.48	0.48
[0, 11]	0.22	0.00	0.00	14.95	0.26	0.26	154.48	0.40	0.39
[0, 12]	2.56	0.06	0.06	9.53	0.17	0.17	108.30	0.28	0.28
[0, 13]	−27.77	−0.63	−0.62	−6.65	−0.12	−0.12	150.75	0.39	0.38
[0, 14]	−14.66	−0.33	−0.33	26.77	0.47	0.46	171.99	0.45	0.44
[0, 15]	−15.76	−0.36	−0.35	9.16	0.16	0.16	118.01	0.31	0.30
[0, 16]	4.79	0.11	0.11	−0.72	−0.01	−0.01	347.20	0.90	0.89
[0, 17]	−9.46	−0.22	−0.21	−4.24	−0.07	−0.07	301.59	0.78	0.77
[0, 18]	−4.73	−0.11	−0.11	2.63	0.05	0.05	257.58	0.67	0.66
[0, 19]	1.86	0.04	0.04	−6.17	−0.11	−0.11	352.18	0.91	0.90
[0, 20]	−15.17	−0.35	−0.34	−15.56	−0.27	−0.27	200.15	0.52	0.51
[0, 21]	−10.70	−0.24	−0.24	6.92	0.12	0.12	295.02	0.76	0.75
[0, 22]	−15.19	−0.35	−0.34	6.93	0.12	0.12	441.70	1.14	1.13
[0, 23]	−12.37	−0.28	−0.28	−13.82	−0.24	−0.24	296.62	0.77	0.76
[0, 24]	−18.30	−0.42	−0.41	−27.68	−0.49	−0.48	340.67	0.88	0.87
[0, 25]	−21.16	−0.48	−0.47	−31.50	−0.56	−0.55	450.46	1.17	1.15
[0, 26]	−16.20	−0.37	−0.36	−38.70	−0.68	−0.67	485.23	1.26	1.24
[0, 27]	−41.21	−0.94	−0.92	−36.03	−0.64	−0.62	377.83	0.98	0.96
[0, 28]	−21.62	−0.49	−0.48	−19.09	−0.34	−0.33	368.60	0.96	0.94
[0, 29]	−33.15	−0.75	−0.74	−17.50	−0.31	−0.30	529.27	1.37	1.35
[0, 30]	−25.48	−0.58	−0.56	−31.59	−0.56	−0.54	390.43	1.01	0.99

Table A44. Case XI: EGARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	−15.06	−0.35	−0.34	36.23	1.06	1.04	−27.65	−0.08	−0.08
[0, 1]	−26.85	−0.63	−0.61	27.21	0.80	0.78	−55.83	−0.16	−0.15
[0, 2]	−18.22	−0.42	−0.42	13.36	0.39	0.38	−33.83	−0.10	−0.09
[0, 3]	−23.86	−0.56	−0.55	−8.40	−0.25	−0.24	30.80	0.09	0.09
[0, 4]	−6.37	−0.15	−0.15	8.97	0.26	0.26	144.80	0.41	0.40
[0, 5]	0.21	0.00	0.00	4.34	0.13	0.13	38.86	0.11	0.11
[0, 6]	−30.78	−0.72	−0.70	−3.30	−0.10	−0.09	84.80	0.24	0.23
[0, 7]	−36.97	−0.86	−0.82	−50.69	−1.49	−1.42	137.52	0.39	0.37
[0, 8]	12.42	0.29	0.28	56.59	1.66	1.63	309.84	0.87	0.86
[0, 9]	3.66	0.09	0.08	28.52	0.84	0.82	228.17	0.64	0.63
[0, 10]	−20.19	−0.47	−0.46	21.11	0.62	0.61	174.51	0.49	0.48
[0, 11]	6.65	0.15	0.15	24.09	0.71	0.70	140.11	0.40	0.39
[0, 12]	9.10	0.21	0.21	19.56	0.57	0.56	92.81	0.26	0.26
[0, 13]	−24.86	−0.58	−0.57	5.31	0.16	0.15	134.74	0.38	0.37
[0, 14]	−14.91	−0.35	−0.34	40.52	1.19	1.16	155.39	0.44	0.43
[0, 15]	−18.07	−0.42	−0.41	24.40	0.72	0.70	100.63	0.28	0.28
[0, 16]	8.31	0.19	0.19	13.80	0.40	0.40	327.76	0.93	0.91
[0, 17]	−4.62	−0.11	−0.11	10.83	0.32	0.31	280.83	0.79	0.78
[0, 18]	3.55	0.08	0.08	17.65	0.52	0.51	235.15	0.66	0.65
[0, 19]	7.85	0.18	0.18	10.40	0.30	0.30	329.01	0.93	0.91
[0, 20]	−11.79	−0.27	−0.27	2.65	0.08	0.08	176.30	0.50	0.49
[0, 21]	−7.92	−0.18	−0.18	26.22	0.77	0.76	270.16	0.76	0.75
[0, 22]	−11.56	−0.27	−0.27	26.89	0.79	0.78	415.58	1.17	1.15
[0, 23]	−7.91	−0.18	−0.18	6.82	0.20	0.20	269.26	0.76	0.75
[0, 24]	−14.70	−0.34	−0.34	−5.88	−0.17	−0.17	312.35	0.88	0.87
[0, 25]	−14.90	−0.35	−0.34	−9.53	−0.28	−0.28	420.59	1.19	1.17
[0, 26]	−11.81	−0.28	−0.27	−15.30	−0.45	−0.44	454.55	1.28	1.26
[0, 27]	−39.72	−0.93	−0.91	−10.90	−0.32	−0.31	346.52	0.98	0.96
[0, 28]	−19.95	−0.46	−0.46	6.90	0.20	0.20	336.14	0.95	0.93
[0, 29]	−32.14	−0.75	−0.73	9.58	0.28	0.28	495.81	1.40	1.37
[0, 30]	−22.72	−0.53	−0.52	−4.08	−0.12	−0.12	355.58	1.00	0.98

Table A45. Case XII: OLS—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	8.05	0.35	0.34	12.44	0.55	0.54	−53.37	−0.64	−0.62
[0, 1]	14.20	0.62	0.61	2.72	0.12	0.12	26.11	0.31	0.31
[0, 2]	−3.48	−0.15	−0.15	−7.99	−0.36	−0.35	−141.36	−1.68	−1.66
[0, 3]	1.66	0.07	0.07	15.48	0.69	0.68	−59.91	−0.71	−0.70
[0, 4]	−1.21	−0.05	−0.05	18.12	0.81	0.79	74.80	0.89	0.88
[0, 5]	3.22	0.14	0.14	−0.03	0.00	0.00	−82.26	−0.98	−0.96
[0, 6]	−2.22	−0.10	−0.09	−13.19	−0.59	−0.57	−51.88	−0.62	−0.60
[0, 7]	−2.27	−0.10	−0.10	−12.32	−0.55	−0.54	47.77	0.57	0.56
[0, 8]	2.53	0.11	0.11	−19.99	−0.89	−0.87	67.84	0.81	0.79
[0, 9]	−23.33	−1.01	−1.00	−18.95	−0.84	−0.83	−55.30	−0.66	−0.65
[0, 10]	−2.55	−0.11	−0.11	−0.14	−0.01	−0.01	−77.17	−0.92	−0.90
[0, 11]	−13.45	−0.59	−0.56	2.36	0.11	0.10	70.02	0.83	0.80
[0, 12]	−3.57	−0.16	−0.15	−8.07	−0.36	−0.35	−79.87	−0.95	−0.93
[0, 13]	−27.30	−1.19	−1.16	−8.14	−0.36	−0.36	−90.11	−1.07	−1.05
[0, 14]	−16.73	−0.73	−0.68	−4.12	−0.18	−0.17	−117.74	−1.40	−1.30
[0, 15]	−2.52	−0.11	−0.11	−12.69	−0.57	−0.56	−69.08	−0.82	−0.81
[0, 16]	−10.96	−0.48	−0.46	−14.44	−0.64	−0.62	−59.47	−0.71	−0.69
[0, 17]	7.21	0.31	0.31	23.28	1.04	1.01	−69.59	−0.83	−0.81
[0, 18]	−3.88	−0.17	−0.17	17.19	0.77	0.75	−76.65	−0.91	−0.90
[0, 19]	−14.73	−0.64	−0.63	−4.20	−0.19	−0.18	63.98	0.76	0.75
[0, 20]	−17.16	−0.75	−0.71	−12.63	−0.56	−0.53	−3.35	−0.04	−0.04
[0, 21]	−37.37	−1.63	−1.57	−19.16	−0.85	−0.82	−57.94	−0.69	−0.66
[0, 22]	−19.02	−0.83	−0.81	−23.06	−1.03	−1.01	−160.49	−1.91	−1.88
[0, 23]	−59.82	−2.60	−2.56	−35.14	−1.57	−1.54	7.46	0.09	0.09
[0, 24]	−55.08	−2.40	−2.35	−6.83	−0.30	−0.30	−10.33	−0.12	−0.12
[0, 25]	−25.88	−1.13	−1.10	2.68	0.12	0.12	−9.90	−0.12	−0.12
[0, 26]	−29.25	−1.27	−1.24	−25.59	−1.14	−1.11	−67.43	−0.80	−0.78
[0, 27]	−50.64	−2.20	−2.13	−32.17	−1.43	−1.39	−64.33	−0.77	−0.74
[0, 28]	−39.20	−1.71	−1.68	−28.83	−1.29	−1.26	74.36	0.89	0.87
[0, 29]	−25.79	−1.12	−1.10	−37.21	−1.66	−1.63	−16.04	−0.19	−0.19
[0, 30]	−32.86	−1.43	−1.41	−33.75	−1.50	−1.48	−56.65	−0.67	−0.66

Table A46. Case XII: GARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	7.57	0.30	0.29	7.48	0.22	0.21	−53.62	−0.56	−0.54
[0, 1]	13.68	0.54	0.53	−0.17	0.00	0.00	24.05	0.25	0.25
[0, 2]	−4.03	−0.16	−0.16	−8.37	−0.25	−0.24	−145.33	−1.51	−1.49
[0, 3]	0.94	0.04	0.04	15.11	0.44	0.44	−65.23	−0.68	−0.67
[0, 4]	−2.22	−0.09	−0.09	15.97	0.47	0.46	68.53	0.71	0.70
[0, 5]	1.93	0.08	0.07	−3.93	−0.12	−0.11	−89.50	−0.93	−0.92
[0, 6]	−3.66	−0.14	−0.14	−16.76	−0.49	−0.48	−60.55	−0.63	−0.61
[0, 7]	−4.13	−0.16	−0.16	−19.91	−0.59	−0.58	38.64	0.40	0.39
[0, 8]	0.59	0.02	0.02	−25.99	−0.77	−0.75	57.02	0.59	0.58
[0, 9]	−25.26	−0.99	−0.97	−22.10	−0.65	−0.64	−68.10	−0.71	−0.70
[0, 10]	−4.72	−0.19	−0.18	−4.24	−0.12	−0.12	−91.11	−0.95	−0.93
[0, 11]	−15.79	−0.62	−0.59	−1.65	−0.05	−0.05	54.71	0.57	0.54
[0, 12]	−6.27	−0.25	−0.24	−14.98	−0.44	−0.43	−95.89	−1.00	−0.98
[0, 13]	−29.98	−1.18	−1.15	−12.10	−0.36	−0.35	−108.14	−1.13	−1.10
[0, 14]	−19.92	−0.78	−0.73	−13.43	−0.40	−0.37	−135.94	−1.41	−1.31
[0, 15]	−5.73	−0.22	−0.22	−19.57	−0.58	−0.57	−89.15	−0.93	−0.91
[0, 16]	−14.33	−0.56	−0.54	−20.98	−0.62	−0.60	−80.98	−0.84	−0.81
[0, 17]	3.53	0.14	0.13	14.33	0.42	0.41	−91.91	−0.96	−0.93
[0, 18]	−7.83	−0.31	−0.30	6.80	0.20	0.20	−100.00	−1.04	−1.02
[0, 19]	−18.89	−0.74	−0.73	−15.14	−0.45	−0.44	39.40	0.41	0.40
[0, 20]	−21.60	−0.85	−0.80	−25.28	−0.74	−0.70	−28.91	−0.30	−0.28
[0, 21]	−42.10	−1.65	−1.59	−33.61	−0.99	−0.95	−84.45	−0.88	−0.85
[0, 22]	−23.47	−0.92	−0.91	−30.21	−0.89	−0.88	−189.95	−1.98	−1.95
[0, 23]	−64.08	−2.52	−2.47	−36.36	−1.07	−1.05	−24.66	−0.26	−0.25
[0, 24]	−60.00	−2.36	−2.31	−15.87	−0.47	−0.46	−42.08	−0.44	−0.43
[0, 25]	−31.07	−1.22	−1.20	−8.04	−0.24	−0.23	−42.62	−0.44	−0.44
[0, 26]	−34.71	−1.36	−1.33	−37.69	−1.11	−1.08	−101.21	−1.05	−1.03
[0, 27]	−56.42	−2.21	−2.14	−46.83	−1.38	−1.33	−98.89	−1.03	−1.00
[0, 28]	−45.31	−1.78	−1.75	−45.91	−1.35	−1.33	38.99	0.41	0.40
[0, 29]	−32.05	−1.26	−1.24	−54.02	−1.59	−1.56	−52.82	−0.55	−0.54
[0, 30]	−39.31	−1.54	−1.52	−50.67	−1.49	−1.47	−94.76	−0.99	−0.97

Table A47. Case XII: GJR(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period $[\tau_1, \tau_2]$	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	7.92	0.34	0.33	8.95	0.38	0.37	−44.93	−0.18	−0.18
[0, 1]	15.00	0.64	0.63	1.31	0.06	0.06	43.30	0.17	0.17
[0, 2]	−1.69	−0.07	−0.07	−6.97	−0.30	−0.29	−115.41	−0.46	−0.46
[0, 3]	4.07	0.17	0.17	16.95	0.72	0.71	−25.30	−0.10	−0.10
[0, 4]	1.55	0.07	0.07	18.61	0.79	0.78	117.99	0.47	0.47
[0, 5]	6.33	0.27	0.27	−0.48	−0.02	−0.02	−30.49	−0.12	−0.12
[0, 6]	1.56	0.07	0.07	−12.94	−0.55	−0.54	8.56	0.03	0.03
[0, 7]	1.52	0.07	0.06	−14.81	−0.63	−0.62	116.69	0.47	0.46
[0, 8]	7.18	0.31	0.30	−20.78	−0.89	−0.87	145.49	0.58	0.57
[0, 9]	−17.64	−0.76	−0.74	−17.05	−0.73	−0.71	31.13	0.12	0.12
[0, 10]	3.61	0.16	0.15	1.45	0.06	0.06	17.87	0.07	0.07
[0, 11]	−6.66	−0.29	−0.27	4.46	0.19	0.18	173.72	0.70	0.67
[0, 12]	3.40	0.15	0.14	−7.82	−0.33	−0.33	32.36	0.13	0.13
[0, 13]	−19.27	−0.83	−0.81	−5.12	−0.22	−0.21	30.90	0.12	0.12
[0, 14]	−8.88	−0.38	−0.35	−4.90	−0.21	−0.19	11.70	0.05	0.04
[0, 15]	6.31	0.27	0.27	−11.10	−0.47	−0.47	69.13	0.28	0.27
[0, 16]	−1.47	−0.06	−0.06	−12.14	−0.52	−0.50	87.40	0.35	0.34
[0, 17]	16.97	0.73	0.71	24.11	1.03	1.00	85.84	0.34	0.34
[0, 18]	6.27	0.27	0.26	17.32	0.74	0.72	87.38	0.35	0.34
[0, 19]	−4.05	−0.17	−0.17	−4.06	−0.17	−0.17	236.64	0.95	0.94
[0, 20]	−6.11	−0.26	−0.25	−13.41	−0.57	−0.54	177.89	0.71	0.67
[0, 21]	−25.98	−1.11	−1.07	−20.93	−0.89	−0.86	131.88	0.53	0.51
[0, 22]	−5.92	−0.25	−0.25	−18.61	−0.79	−0.78	38.30	0.15	0.15
[0, 23]	−45.22	−1.94	−1.90	−25.56	−1.09	−1.07	215.15	0.86	0.85
[0, 24]	−41.03	−1.76	−1.73	−2.99	−0.13	−0.13	205.69	0.83	0.81
[0, 25]	−11.46	−0.49	−0.48	5.62	0.24	0.23	214.70	0.86	0.85
[0, 26]	−14.43	−0.62	−0.60	−23.29	−0.99	−0.97	165.77	0.67	0.65
[0, 27]	−35.58	−1.53	−1.48	−31.47	−1.34	−1.30	177.41	0.71	0.69
[0, 28]	−23.89	−1.02	−1.01	−29.60	−1.26	−1.24	324.66	1.30	1.28
[0, 29]	−9.81	−0.42	−0.41	−37.33	−1.59	−1.56	242.93	0.97	0.96
[0, 30]	−16.29	−0.70	−0.69	−33.52	−1.43	−1.41	210.96	0.85	0.83

Table A48. Case XII: EGARCH(1,1)—Cumulative abnormal change rate of Chinese tourist arrivals.

Event Period [τ_1, τ_2]	Group-Type			Individual-Type			Medical-Type		
	CAR	t-Value		CAR	t-Value		CAR	t-Value	
		TM	SRM		TM	SRM		TM	SRM
[0, 0]	7.52	0.34	0.33	9.07	0.32	0.31	−51.44	−0.62	−0.60
[0, 1]	14.31	0.65	0.64	2.88	0.10	0.10	27.08	0.33	0.32
[0, 2]	−2.66	−0.12	−0.12	−3.87	−0.14	−0.13	−141.52	−1.70	−1.67
[0, 3]	2.78	0.13	0.12	21.11	0.74	0.73	−60.17	−0.72	−0.71
[0, 4]	−0.10	0.00	0.00	23.49	0.82	0.81	75.17	0.90	0.89
[0, 5]	4.34	0.20	0.19	5.13	0.18	0.18	−81.28	−0.98	−0.96
[0, 6]	−0.75	−0.03	−0.03	−6.21	−0.22	−0.21	−51.15	−0.61	−0.60
[0, 7]	−1.17	−0.05	−0.05	−7.78	−0.27	−0.27	50.05	0.60	0.59
[0, 8]	4.18	0.19	0.19	−12.40	−0.43	−0.43	69.37	0.83	0.82
[0, 9]	−20.91	−0.95	−0.94	−7.06	−0.25	−0.24	−55.04	−0.66	−0.65
[0, 10]	0.01	0.00	0.00	12.31	0.43	0.42	−76.62	−0.92	−0.90
[0, 11]	−10.59	−0.48	−0.46	16.39	0.57	0.55	70.43	0.85	0.81
[0, 12]	−0.89	−0.04	−0.04	4.62	0.16	0.16	−78.38	−0.94	−0.92
[0, 13]	−23.84	−1.09	−1.06	8.94	0.31	0.31	−89.94	−1.08	−1.06
[0, 14]	−13.86	−0.63	−0.59	9.21	0.32	0.30	−115.48	−1.39	−1.29
[0, 15]	1.05	0.05	0.05	4.51	0.16	0.16	−67.91	−0.82	−0.80
[0, 16]	−7.05	−0.32	−0.31	4.60	0.16	0.16	−58.55	−0.70	−0.68
[0, 17]	11.03	0.50	0.49	41.46	1.45	1.41	−67.78	−0.81	−0.79
[0, 18]	−0.02	0.00	0.00	35.44	1.24	1.22	−74.35	−0.89	−0.88
[0, 19]	−10.66	−0.49	−0.48	15.02	0.53	0.52	66.40	0.80	0.79
[0, 20]	−13.08	−0.60	−0.56	6.41	0.22	0.21	−0.34	0.00	0.00
[0, 21]	−33.30	−1.52	−1.46	−0.40	−0.01	−0.01	−54.29	−0.65	−0.63
[0, 22]	−13.44	−0.61	−0.60	4.36	0.15	0.15	−159.93	−1.92	−1.89
[0, 23]	−52.97	−2.41	−2.37	−0.40	−0.01	−0.01	5.48	0.07	0.06
[0, 24]	−49.23	−2.24	−2.20	21.74	0.76	0.75	−9.21	−0.11	−0.11
[0, 25]	−20.00	−0.91	−0.89	31.09	1.09	1.07	−8.19	−0.10	−0.10
[0, 26]	−23.32	−1.06	−1.04	2.97	0.10	0.10	−65.27	−0.78	−0.76
[0, 27]	−44.83	−2.04	−1.98	−4.63	−0.16	−0.16	−61.22	−0.74	−0.71
[0, 28]	−33.50	−1.53	−1.50	−2.16	−0.08	−0.07	78.36	0.94	0.93
[0, 29]	−19.75	−0.90	−0.88	−8.78	−0.31	−0.30	−12.25	−0.15	−0.14
[0, 30]	−26.55	−1.21	−1.19	−3.93	−0.14	−0.14	−52.92	−0.64	−0.63

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Why Are Warrant Markets Sustained in Taiwan but Not in China?

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Abstract: This paper uses moment analysis, capital asset pricing model (CAPM) statistics, stochastic dominance (SD) test, and volume analysis to investigating why the market for Taiwan warrants can be sustained but not in China. Our moment analysis shows that buying in China warrants has a higher likelihood of losses. Our CAPM analysis shows that both the Sharpe ratio and Jensen index for warrants from the Chinese market are too negative. The Treynor index shows that Chinese warrants are highly volatile. Our SD analysis shows that risk averters prefer to invest in Chinese warrants compared to Taiwanese warrants, implying that the warrant issuers prefer to issue Taiwanese warrants than Chinese warrants. Using volume analysis, the Chinese warrant market is much more active, implying more speculative activities in China than in Taiwan. All the above could lead to China's decision to close its warrant market. The findings in the paper are useful for academics, investors, and policy makers.

Keywords: moment analysis; CAPM statistics; stochastic dominance; volume analysis; arbitrage opportunity; market efficiency; warrants; China market; Taiwan market

1. Introduction

This paper compares investor preferences between the two largest warrant markets in Greater China, namely Mainland China and Taiwan. Both markets are politically, economically, and financially competitive, and always seem to be catching the eyes of the world. The comparison period was chosen such that China was experiencing reforms and opening up the securities market, while Taiwan was in the process of party rotation and economic transformation.

Warrants are one of the most commonly traded financial products in financial markets internationally. China has been developing its stock markets very well, to be one of the largest stock markets in the world, while the Taiwanese stock market is much smaller, being ranked in the top 20 stock exchanges, according to various international databases (see, for example, http://www.visualcapitalist.com/20-largest-stock-exchanges-world/). On the other hand, the market for warrants, which was initiated in 1997, is financially successful in Taiwan, while the market for warrants in China, which was initiated in 2004, was prevalent in Mainland China, especially in 2006, but closed in 2010. For this reason, among others, it is interesting to study why the market of warrants in China was prevalent in Mainland China, especially in 2006, but closed in 2010.

Most of the warrants traded in China by the end of 2008 were covered warrants, connected with the flotation of non-tradable shares (the Chinese share reform started in 2005, with two share types, tradable shares and non-tradable shares, before the reform). The unique characteristics of Chinese warrants and irrational investor behavior in the Chinese warrant market are important in the financial literature. Therefore, it is interesting to study investor performance and risk preference in the Chinese warrant market. In the case of warrants in China, the warrants can be calls or puts.

When call options are exercised by investors, non-tradable shares are issued by the Chinese company, leaving the total number of outstanding shares unchanged. Therefore, there is no issue about dilution of earnings when warrants are exercised. In this aspect, warrants in China are similar to covered warrants in Europe and Asia. However, covered warrants in Europe and Asia are issued by third parties, such as banks, whereas in China, most warrants are issued by separate companies.

After the stock reforms in 2005, China's equity warrants market became the second largest in the world in terms of trading value, after Germany, surpassing Hong Kong in 2006. The growth in the warrants market in China has been constrained by the gradual expiration of reform-related warrants, excessive speculation, and a lack of understanding of the warrants market by its participants. The mechanism for creating special warrants designed as a transition to the development of covered warrants has been under hot debate. A more refined regulatory framework and a stronger institutional investor base are needed, and are prerequisites for a smoothly-functioning warrants market.

In order to foster the long-term development of the warrants market in China, financial experts have argued that issuing covered warrants is crucial, together with proper regulation. Domestic brokerages and exchanges have been lobbying the Chinese government to approve the issuance of covered warrants in a more formal setting. Securities firms argue that allowing brokers to launch covered warrants will significantly boost supply. That is, it is expected that the covered warrants will help in pricing securities more efficiently, thereby increasing the market depth of both the warrant and underlying stock markets. At the same time, it may effectively help curb the current speculative sentiment in China's financial markets.

The split-share structure was a legacy of China's initial share issue privatization (SIP), in which state-owned enterprises (SOEs) went public to issue minority tradable shares to institutional and individual investors. On the other hand, the Chinese government withheld control of these listed SOEs by owning majority non-tradable shares. Although the split-share structure played a positive role in facilitating the SIP, it jeopardized China's continued privatization efforts by restricting the tradability of state-owned shares in the secondary market, and also caused serious corporate governance problems, encouraged speculation in the stock market, and blocked mergers and acquisitions.

In 2005, the Split-Share Structure Reform was initiated to dismantle the dual share structure by converting non-tradable shares into tradable shares. The reform effectively removed the legal and technical obstacles of transferring state-owned shares to public investors, opening up the gate to China's secondary privatization which, in contrast to the initial SIP, would further liberalize state-owned shares in full circulation.

However, there have been very few studies, if any, comparing the Chinese and Taiwanese warrant markets in which both the main participants of securities markets are individual investors or corporate investors. The Taiwanese warrant market was established in 1997, while the Chinese warrant market began in 2004. The background of the developing warrant market in Taiwan is to provide diversified investment and hedging tools compared with a tool of compensation in the share reforms in China. The Chinese warrant market became the largest warrant market in the world in terms of trading volume in 2006, shortly after its inception. In 2006, the Taiwanese warrant market was ranked at number 9 according to the total trading volume provided by the World Federation of Exchanges (WFE).

Although Greater China shares a common culture, the background of developing warrant markets are different in China and Taiwan. In the period 2004 to 2008, Taiwan's economy faced a huge problem because of industry transformation, with many entrepreneurs moving their factories to Mainland China. In addition, Taiwan experienced the first party transition and the ruling party was politically against Chinese authority, while Mainland China was devoted to the reform and opened its market at the same time. Therefore, in addition to political competition between Taiwan and Mainland China, the two economies were also facing industrial competition. Economic development will be reflected in the performance of the securities markets. Among other reasons, it will be interesting to compare the warrant markets in China and Taiwan.

In order to compare the Chinese and Taiwanese warrant markets, there are several differences that are worth mentioning. First, China developed its warrant market in 2004 mainly for the purpose of the share-split reform, which was intended to allow government-held non-tradable shares to become tradable in the market. In order to make up possible losses of original tradable shareholders, some corporations issued warrants and granted these warrants as compensation. However, the warrants in Taiwan and Hong Kong are issued by third parties, that is, securities corporations, and not by the corporations themselves. Securities corporations issue warrants, sell them to investors, and hedge by buying underlying stocks. Second, the Taiwanese warrant market was established in 1997, 7 years earlier than the Chinese warrant market.

In addition, they also play roles of market makers to facilitate market liquidity. In China, corporations themselves issue warrants based on their non-tradable stocks as underlying stocks, and neither hedge nor play as market makers. Third, the number of issued warrants in the two markets differs substantially. In China, there were only 55 warrants traded in the market, but the trading volume was once ranked as the largest in the world. In Taiwan, the warrant market experienced rises and falls, and currently there are more than 10 thousand warrants issued every year. Moreover, Taiwan has both vanilla and exotic types of warrants, while China has only vanilla-type warrants.

Finally, the transaction mechanism in the two markets are different. In Taiwan, trading warrants are similar to trading stocks in terms of trading rules and transaction costs. However, it is distinct from trade stocks and trade warrants in China. The detailed mechanism of the Chinese warrant market is described below.

The Chinese warrant market attracted a lot of funds from investors and became the largest in the world in terms of total trading volume, even though there were only 55 warrants in the market. The high turnover of warrants in China could be attributed to the warrants "T+0" trading rule, high volatility, and exemption from transaction taxes. Warrants were the only security in China with a "T+0" trading mechanism, that is, investors are able to sell warrants on the same trading day when they are purchased. On the other hand, stocks could only be sold on the next trading day (that is, the "T+1" rule).

Additionally, stock prices are restricted to fluctuate within 10% of the closing price on the previous trading day, while the range was usually over 25% of the closing price for the warrant on the preceding trading day. Moreover, trading in warrants was exempted from the 0.2% to 0.3% transaction tax or stamp duty, and hence trading warrants benefits from a tax advantage. These special characteristics provided greater flexibility for investors on trading warrants. Therefore, warrants were the only securities for intraday trading, and hence attracted significant trading activities.

In this paper, we bridge a gap in the literature by using moment analysis, CAPM statistics, SD test, and volume analysis to examine investor preferences for warrants between China and Taiwan, and investigate why the market for Taiwan warrants can be sustained but not in China. Using moment analysis, buying Chinese warrants has a much higher opportunity for making losses as compared with Taiwan. This could make investors avoid investing in Chinese warrants which, in turn, could lead to the closure of the market for warrants.

Using CAPM analysis, we conclude that, in general, both the Sharpe ratio and Jensen index for warrants from the Taiwanese market are more attractive financially, while the Chinese market is too negative. On the other hand, the Treynor index for Chinese warrants shows that they are highly volatile. Therefore, China closed its warrant market after the end of the share-split reform, where the warrants expired completely in 2010.

Based on SD analysis, it can be inferred that there are no arbitrage opportunities between the Chinese and Taiwanese warrant markets, the markets of Chinese and Taiwanese warrants are not efficient, and second- and third-order risk averters prefer to invest in China compared with Taiwan. This implies that warrant issuers prefer to Taiwanese warrants to their counterparts in China. This could be another reason why the market for Taiwanese warrants can be sustained but not in China.

Using volume analysis, the Chinese warrant market is clearly much more active than the Taiwanese warrant market. This could imply that there are more speculative activities in China than in Taiwan which, in turn, could lead to China's decision to close its warrant market. The findings in the paper are important for investors for their investment decisions regarding Taiwanese and Chinese warrants, challenging to academics for their study on modeling Taiwan and China warrants, and useful for policy makers for their policy making related to Taiwan and China warrants. In the future, China should seriously reconsider reopening its warrant market and learning from mature-covered warrant markets, such as Taiwan's, on how to inhibit excess speculation and to educate warrant investors.

The remainder of the paper is organized as follows. Section 2 briefly reviews the literature pertaining to covered warrants and the stochastic dominance rules, as well as the rationale behind the SD tests. The data, sample characteristics, and methodology are discussed in Section 3. The empirical results are analysed in Section 4, while Section 5 gives some concluding remarks.

2. Literature Review

Many studies have investigated Chinese and Taiwanese warrant markets. For example, Xiong and Yu [1] find that the daily trading volume of many warrants is more than 3 times that of the issuance volume, even though this put warrants extremely out of money between 2005 and 2008. The market is useful for examining price bubbles because of observable underlying stock prices and the limited life of the warrants to determine the values of the associated contingent claims. Bubbles can be used to test bubble theories, such as rational bubbles, agency problems, gambling behaviour, resale option theory, non-common knowledge of rationality, feedback loop theory, among other interesting topics. The authors conclude that short selling restrictions and heterogeneous beliefs drive bubbles.

Some previous studies have focused on issuance, hedging, and expiration effects of warrants on stock returns [2–5]. For example, Chung et al. [5] examine the impact of covered warrant hedging on underlying stocks on the Taiwan Stock Exchange. They find significant positive abnormal returns and trading volume before the announcement of issuing warrants, especially for large hedging demand warrants. Their findings show that stock return volatility is positively related to the price elasticity of hedging demand.

Additionally, the authors discover a significant negative effect on stock prices after a call warrant has expired in-the-money because of the liquidation of the hedging portfolio. In China, Liao and Chen [4] find that the expiration of call warrants has a significantly negative price effect during the last four days of the exercise period, whereas the expiration of put warrants exhibits no significant price effects. Overall, the trading activities of call warrants have a more profound effect than their put counterparts around the expiration day.

Previous studies have also compared the prices of warrants and options with the same underlying stocks. For instance, Li and Zhang [6] and Chan and Pinder [7] find derivative warrants generally have higher prices than corresponding options, with the price differences reflecting the liquidity premiums of derivative warrants over options in the Hong Kong and Australian markets, respectively. Horst and Veld [8] compare the price differences between 16 Euronext Amsterdam options and warrants, and find that investors may perceive warrants as another type of instrument, and that the warrants are over-priced over the first five trading days.

Bartram and Fehle [9] examine the degree of the bid-ask spread between warrants and options in Germany, and find that, with overlapped underlying, both warrants and options experienced lower bid-ask spreads due to competition between options and warrants. Petrella [10] examines the bid-ask spread of covered warrants in Italy, and finds that the reservation spread plays an important role in determining the warrant spreads that are connected with the underlying spreads.

As the Chinese warrant market is relatively young and speculative, investors have largely participated in the market for its special characteristics, namely the speculative behaviour of retail investors in Chinese warrant markets [1]. Additionally, speculative activities in the warrant market can be contagious and spill over across stock markets [11]. Tang and Wang [12] examine warrant return properties, volatility behaviour, and pricing errors, and document a stylized fact that call warrants have considerable linkage with their underlying financial assets, but put warrants have almost none.

The combination of the arbitrage pricing theory and the resale-option bubble theory proposed by Scheinkman and Xiong [13] is adopted to explain this stylized fact. In addition, Liao et al. [14] examine the incidence of two types of irrational exercise behaviour in the Chinese warrants market and find that 121.64 million shares of warrants were either exercised with an immediate loss, or failed to be exercised because of warrant holder ignorance and/or negligence of warrant mechanics.

Furthermore, several studies analysed pricing errors of warrants and hedging risks. For example, Chang et al. [15] find that the market price of warrants is far higher than the prices from Black–Scholes models using historical volatilities. In addition, warrant prices and their underlying stock prices are not monotonic, perfectly correlated, and follow option redundancy properties. Cumulative delta hedge profits for most mature warrants are negative, and these negative profits are mainly from volatility risks, trading value of put warrants, and market risk of call warrants.

Powers and Xiao [16] adopt three standard pricing models and document that put warrant market prices averaged 1.2 yuan more than model-generated prices (over-priced), while call warrant prices averaged 1.9 yuan less (under-priced). The authors explain the mispricing due to an implicit discount on the value of stocks when pricing warrants as investors take the potential burst of a stock market bubble into account and a premium on warrants to fulfill speculation purpose or tax advantage.

Liao et al. [17] observe that creation mechanics (that is, increasing the supply of securities) similar with the short-selling property is useful for reducing bubble issues in Chinese warrant markets but additional warrant supply can only reduce instead of eliminating bubbles. Fung et al. [18] review the development of the China warrants market, and highlight the issues of over-speculation and lacking of recognition of participants. The authors suggest that the market requires a more regulated structure and more institutional investors as the cornerstone of the market.

Some studies have applied mean variance (MV), CAPM, and SD to warrant markets. For example, Chan et al. [19] examine in the UK covered warrants market by using SD. Their empirical results show that neither covered warrants nor their underlying shares stochastically dominate each other, implying both markets are efficient. They also find that UK covered warrant returns efficiently reflect the return information of the underlying shares from a likelihood ratio (LR) test. As distinct from their analysis on warrants and their underlying shares, we compare warrants in the Chinese and Taiwanese markets with similarities (for example, retail investors are main market participants) and differences (for example, the issuers are share-reform companies in China and securities companies in Taiwan) in terms of stochastic dominance.

A variety of interesting papers have applied the MV rule, CAPM statistics, and SD tests to examine the performance of other markets. For example, applying the SD test and other techniques, Abid et al. [20] investigate the performance of different option strategies; Qiao et al. [21,22] and Lean et al. [23,24] evaluate the relationship between spot and futures prices; Bouri et al. [25] study the role of wine investment within a portfolio of different assets; Qiao and Wong [26] and Tsang et al. [27] examine whether the housing market in Hong Kong is efficient; Hoang et al. [28–30] and Khamlichi et al. [31] examine the role of gold in the diversification of portfolios; Vieito et al. [32] and Zhu et al. [33] investigate whether the financial crisis had any positive impacts on stock markets; Broll et al. [34,35] analyse banks behaviour; Egozcue and Wong [36], Egozcue et al. [37], Abid et al. [38], and Lozza et al. [39] examine investor behaviour in diversification; Fong et al. [40,41] and Lean et al. [42] study investor behaviour in stock markets; Ma and Wong [43], Alghalith et al. [44], Guo et al. [45], and Niu et al. [46] examine different risk measures; and Chiang et al. [47] and Lean et al. [48] evaluate the performance of different funds.

3. Data and Methodology

3.1. Data

The warrant data are obtained from the Taiwan Economic Journal (TEJ). There are 55 warrants listed in the Shanghai and Shenzen Stock Exchanges between 2005 and 2009 (65 warrants were issued in the period, but only 55 of them were listed). For comparison, we randomly select 44 covered warrants of which the underlying stocks are in the list of the Taiwan 50 index in the same period (from 2005 to 2009, 44 of the top 50 Taiwan companies were issued corresponding warrants) (Since the listed Chinese warrants belong to large firms in China, we choose the warrants of the largest 50 firms from Taiwan 50 index constituents for comparison. However, in the corresponding period of Chinese warrants, there were only 44 firms in Taiwan with warrants issued. Thus, we randomly select 1 warrant for each firm (in Taiwan, all securities companies can issue warrants for the same firm and hence one firm can have more than 1 warrant)). The daily data include tickers, warrant prices, underlying stock prices, adjusted strike prices, data dates, issuance dates, maturity dates, and others. The conclusions are drawn based on the selected data.

Chinese and Taiwanese warrants are denoted by C and T, respectively. As there are too many warrants in both the Chinese and Taiwanese markets, we follow Wong et al. [49] in selecting the most representative warrants that have the maximum and minimum values of the of mean, standard deviation, and Sharpe ratio for both China and Taiwan. In addition, we include the maximum and minimum of the beta value, Jensen index, and Treynor index for both China and Taiwan.

The China warrants are denoted as: C06 for the minimum Sharpe ratio; C12 for the maximum Treynor index; C14 for the minimum mean and the minimum Jensen index; C23 for the maximum mean, the maximum Sharpe ratio, and the maximum Jensen index; C44 for the minimum standard deviation; C47 for the maximum standard deviation and the minimum beta value; C52 for the maximum beta value; and C55 for the minimum Treynor index.

The Taiwanese warrants are denoted as: T1 for the minimum Jensen index; T12 for the maximum standard deviation; T13 for the minimum mean; T15 for the minimum Sharpe ratio; T17 for the minimum standard deviation, the maximum Sharpe ratio, the minimum beta value, and the maximum Treynor index; T25 for the minimum Treynor index; T26 for the maximum beta value; and T33 for the maximum mean and the maximum Jensen index.

3.2. Methodology

In this paper, we use the MV rule, CAPM statistics, SD test, and volume analysis to examine the investor preferences towards the warrants between China and Taiwan. We first discuss the MV rule in the following subsection.

3.2.1. Mean-Variance (MV) Criteria

Define U_j as the set of utility functions such that:

$$U_j = \{u : (-1)^{i+1} u^{(i)} \geq 0, i = 1, \cdots, j\} \tag{1}$$

where $u^{(i)}$ is the ith derivative of the utility function U.

For the returns Y and Z of any two assets or portfolios with means μ_y and μ_z and standard deviations σ_y and σ_z, respectively, the MV rule (Markowitz [50]; Bai, et al. [51]; Leung, et al. [52]) is such that Y is said to dominate Z if $\mu_y \geq \mu_z$ and $\sigma_y \leq \sigma_z$, and if the inequality holds in at least one of the two conditions. Wong [53] and Guo and Wong [54] show that if Y dominates Z by the MV rule, denoted by $Y \succ_{MV} Z$, then risk averters with $u^{(1)} > 0$ and $u^{(2)} < 0$ will attain higher expected utility by holding Y than Z under certain conditions. The theory can be extended to non-differentiable utilities (see Wong and Ma, [55]).

3.2.2. Stochastic Dominance (SD) Approach

Let Y and Z represent the returns of two assets or portfolios with a common support of $\Omega = [a, b]$ $(a < b)$, cumulative distribution functions (CDFs), F and G, and corresponding probability density functions (PDFs), f and g, respectively, so that we define:

$$H_0 = h, H_j(x) = \int_a^x H_{j-1}(t)dt \tag{2}$$

for $h = f,\ g$; $H = F,\ G$; for any integer j.

We call the integral H_j the jth-order integral for $H = F,\ G$. Y is said to dominate Z by FSD (SSD, TSD), denoted by $Y \succ_1 Z$ $(Y \succ_2 Z,\ Y \succ_3 Z)$, if $F_1(x) \leq G_1(x)$ $(F_2(x) \leq G_2(x),\ F_3(x) \leq G_3(x))$ for all possible returns x, and the strict inequality holds for at least one small open interval of x, where FSD (SSD, TSD) denotes first-order (second-order, third-order) SD, respectively. For $Y \succ_3 Z$, we need a further condition: $\mu_Y \geq \mu_Z$ (see Sriboonchitta et al. [56], Levy [57], Guo and Wong [54]), and the references listed therein, for further information on the SD definitions for any order.

The SD tests have been well developed (Davidson and Duclos, DD, [58]; Bai, et al. [59,60]; Ng, et al. [61]) to allow statistical significance to be determined. The SD test developed by DD is found to be powerful, less conservative in size, and robust to non-iid and heteroscedastic data (Lean et al., [62]). As Bai et al. [59] derive the limiting process of the DD statistic when the underlying processes are dependent or independent, we use their SD tests in the empirical analysis.

Let $\{f_i\}(i = 1,\ 2, \cdots n_f)$ and $\{g_i\}$ $\left(i = 1,\ 2, \cdots n_g\right)$ be observations drawn from the returns of any two assets or portfolios, Y and Z, with CDFs F and G, respectively. For a grid of pre-selected points x_1, $x_2, \ldots\ x_k$, the jth-order SD test statistic, $T_j(x)$ (j = 1, 2, and 3), is defined as:

$$T_j(x) = \frac{\hat{F}_j(x) - \hat{G}_j(x)}{\sqrt{\hat{V}_j(x)}} \tag{3}$$

where

$$\hat{V}_j(x) = \hat{V}_{F_j}(x) + \hat{V}_{G_j}(x) - 2\hat{V}_{FG_j}(x);\ \hat{H}_j(x) = \frac{1}{N_h(j-1)!}\sum_{i=1}^{N_h}(x - h_i)_+^{j-1}, \tag{4}$$

$$\begin{aligned} \hat{V}_{H_j}(x) &= \tfrac{1}{N_h}\left[\tfrac{1}{N_h((j-1)!)^2}\sum_{i=1}^{N_h}(x-h_i)_+^{2(j-1)} - \hat{H}_j(x)^2\right],\ H = F, G;\ h = f, g; \\ \hat{V}_{FG_j}(x) &= \tfrac{1}{N_h}\left[\tfrac{1}{N_h((j-1)!)^2}\sum_{i=1}^{N_h}(x-f_i)_+^{j-1}(x-g_i)_+^{j-1} - \hat{F}_j(x)\hat{G}_j(x)\right], \end{aligned} \tag{5}$$

F_j and G_j are defined in (2). For all $i = 1,\ 2, \ldots, k$, we test the following hypotheses:

Hypothesis 1 (H1). $F_j(x_i) = G_j(x_i),\ for\ all\ x_i.$

Hypothesis 2 (H2). $F_j(x_i) \neq G_j(x_i)\ for\ some\ x_i.$

Hypothesis 3 (H3). $F_j(x_i) \leq G_j(x_i)\ for\ all\ x_i,\ F_j(x_i) < G_j(x_i)\ for\ some\ x_i.$

Hypothesis 4 (H4). $F_j(x_i) \geq G_j(x_i)$ *for all* x_i, $F_j(x_i) > G_j(x_i)$ *for some* x_i.

Not rejecting either H1 or H2 implies the non-existence of any SD relationship between Y and Z. If H3 (H4) of order one is accepted, then $Y(Z)$ stochastically dominates $Z(Y)$ at first order, denoted by $Y \succ_1 Z$ $(Z \succ_1 Y)$. If H3 (H4) is accepted at order two [three], then $Y(Z)$ stochastically dominates $Z(Y)$ at second order, denoted by $Y \succ_2 Z$ $(Z \succ_2 Y)$, $[Y \succ_3 Z$ $(Z \succ_3 Y)]$. Readers may refer to Bai et al. [59] for the decision rules and further information on the tests, and Chan et al. [63] for testing the third-order SD.

Bai et al. [59] derive the limiting process of the SD statistic $T_j(x)$ so that the SD test can be performed by using $\max_x |T_j(x)|$ to account for the dependency of the partitions. We follow their recommendation in the empirical analysis. As Fong et al. [41], Lean et al. [48,62], among others, recommend a limited number (100) of grids for comparison, we adopt their suggestion. In order to minimize Type II errors and to accommodate the effect of almost SD (Leshno and Levy [64]; Guo, et al. [65–67]), we follow Gasbarro et al. [68], Clark et al. [69], among others, to use a conservative 5% cut-off point in examining the proportion of test statistics to draw inferences.

4. Empirical Results

This section discusses the empirical results. We use moment analysis, CAPM statistics, SD test, and volume analysis to examine investor preferences for warrants between China and Taiwan, and investigate why the market for Taiwanese warrants can be sustained but not in China. We note that the moment analysis (Chan et al. [70]) includes the mean-variance (MV) rule and the analysis of higher-order moments.

4.1. Moments Analysis

The MV rule is used to examine the performance between Chinese and Taiwanese warrants. In order to do so, we examine the descriptive statistics of daily excess returns in Table 1 and the results of the t and F tests in Table 2 for selected Chinese and Taiwanese warrants.

Table 1. Summary statistics and CAPM using daily excess returns for selected Chinese and Taiwanese warrants.

Warrant Code	Mean	Std. Dev.	Skewness	Kurtosis	JB	Sharpe	Beta	Treynor	Jensen
C06	−0.0201	0.0781	−3.7196	33.9411	10084.75	−0.2579	0.0150	−1.3384	−0.0186
C12	−0.0186	0.1440	−13.0898	242.2479	1160912.00	−0.1294	−0.0009	20.5741	−0.0183
C14	−0.0638	0.2956	−8.3235	80.9023	30407.42	−0.2157	−0.0059	10.8959	−0.0624
C23	0.0011	0.0555	0.4351	5.1238	52.02	0.0204	0.0175	0.0647	−0.0056
C44	−0.0057	0.0300	2.7879	24.6026	6885.69	−0.1527	0.0115	−0.4943	−0.0058
C47	−0.0365	0.3155	−13.5417	197.7772	377048.90	−0.1158	−0.0174	2.0965	−0.0298
C52	−0.0270	0.2297	−13.2963	195.6075	373322.80	−0.1175	0.0397	−0.6796	−0.0405
C55	−0.0189	0.1171	−2.2507	29.5247	7117.58	−0.1615	0.0003	−60.9548	−0.0190
T1	−0.0511	0.2409	−0.4242	12.6574	454.26	−0.2121	0.0814	−0.6280	−0.0565
T12	−0.0341	0.4486	−0.0494	20.9576	1679.60	−0.0760	0.0289	−1.1812	−0.0307
T13	−0.0573	0.2730	1.3731	15.5192	800.82	−0.2100	0.0232	−2.4702	−0.0560
T15	−0.0374	0.1388	−2.2828	22.0487	2925.68	−0.2693	0.0225	−1.6632	−0.0343
T17	0.0053	0.0588	1.9440	11.7270	475.41	0.0892	0.0056	0.9310	0.0037
T25	−0.0434	0.1742	0.2863	11.0227	336.94	−0.2491	0.0103	−4.2091	−0.0441
T26	−0.0032	0.2247	0.9245	5.1186	41.19	−0.0144	0.1324	−0.0245	−0.0109
T33	0.0128	0.1545	−1.0409	10.6930	320.22	0.0829	0.0523	0.2451	0.0094

Notes: C06—min Sharpe; C12—max Treynor; C14—min mean, min Jensen; C23—max mean, max Sharpe & max Jensen; C44—min s.d.; C47—max s.d., min beta; C52—max beta; C55—min Treynor; T1—min Jensen; T12—max s.d.; T13—min mean; T15—min Sharpe; T17—min s.d., max Sharpe, min beta, max Treynor; T25—min Treynor; T26—max beta; T33—max mean & max Jensen.

Table 2. MV Results for selected pairwise comparison.

Pairwise Comparison	*t* Test	*F* Test	MV Dominance
C14-T13	$\mu_C < \mu_T$ -0.1474	$\sigma_C > \sigma_T$ 1.1529	No
C23-T33	$\mu_C < \mu_T$ -1.041	$\sigma_C < \sigma_T$ 7.7611 ***	C23 $\succ_{MV}$ T33
C44-T17	$\mu_C < \mu_T$ -2.6106 ***	$\sigma_C < \sigma_T$ 3.8564 ***	No
C47-T12	$\mu_C < \mu_T$ -0.0597	$\sigma_C < \sigma_T$ 2.0222 ***	C47 $\succ_{MV}$ T12
C06-T15	$\mu_C > \mu_T$ 1.6191	$\sigma_C < \sigma_T$ 3.1598 ***	C06 $\succ_{MV}$ T15
C23-T17	$\mu_C < \mu_T$ -0.6578	$\sigma_C < \sigma_T$ 1.1249	No
C47-T17	$\mu_C < \mu_T$ -1.4663	$\sigma_C > \sigma_T$ 28.7523 ***	C47 $\succ_{MV}$ T17
C52-T26	$\mu_C < \mu_T$ -0.9425	$\sigma_C > \sigma_T$ 1.0449	No
C55-T25	$\mu_C < \mu_T$ 1.5869	$\sigma_C < \sigma_T$ 2.2131 ***	C55 $\succ_{MV}$ T25
C12-T17	$\mu_C < \mu_T$ -1.8125 *	$\sigma_C > \sigma_T$ 5.9872 ***	T17 $\succ_{MV}$ C12
C23-T01	$\mu_C > \mu_T$ 3.1743 ***	$\sigma_C < \sigma_T$ 18.8615 ***	C23 $\succ_{MV}$ T01
C14-T33	$\mu_C < \mu_T$ -2.4578 **	$\sigma_C > \sigma_T$ 3.5309 ***	T33 $\succ_{MV}$ C14

Notes: C14-T13 is the pair of mean min, C23-T33 is the pair of mean max; C44-T17 is the pair of s.d min, C47-T12 is the pair of s.d max; C06-T15 is the pair of Sharpe ratio min, C23-T17 is the pair of Sharpe ratio max; C47-T17 is the pair of beta min, C52-T26 is the pair of beta max; C55-T25 is the pair of Treynor ratio min, C12-T17 is the pair of Treynor ratio max; C23-T01 is the pair of Jensen ratio min, C14-T33 is the pair of Jensen ratio max. ***, ** and * denotes significant at 1%, 5% and 10% levels respectively.

We compare warrants with minimum daily excess returns from China and Taiwan, which are represented by C14 and T13, respectively. From Table 1, the mean excess return of T13 is higher than that of C14, while the standard deviation of the former is smaller. However, the insignificant t and F statistics in Table 2 conclude there is no MV dominance between T13 and C14 using the MV approach. We also compare warrants with maximum daily excess returns from China and Taiwan, which are represented by C23 and T33, respectively. Although T33 has larger mean excess returns, it also has a higher standard deviation than C23. Therefore, there is no MV dominance between T33 and C23 using the MV approach.

Next we compare warrants with minimum (maximum) daily standard deviations from China and Taiwan, which are represented by C44 and T17 (C47 and T12), respectively. It is found that T17 has significantly higher mean excess return and significantly higher standard deviation than C44, so there is no MV dominance between T33 and C23 using the MV approach. However, T12 has insignificantly higher mean excess return and significantly higher standard deviation than C47, implying that C47 dominates T12 using the MV approach. With the MV criterion, we find that five pairs of China warrants dominate Taiwan warrants, and three pairs of Taiwanese warrants dominate Chinese warrants. The other four pairs have not shown any dominance between Chinese and Taiwanese warrants.

Tables 1 and 2 indicate the following. First, the mean excess returns are, in general, higher for Taiwanese warrants, while most of the mean excess returns for both Chinese and Taiwanese warrants are negative, which implies that the mean excess returns of Chinese warrants are more negative.

This could make investors avoid investing in Chinese warrants which, in turn, could lead to the closure of the Chinese warrant market.

In addition, most of the Chin ese warrants are significant and negatively skewed, while most of the Taiwan ese warrants are either significantly and positively skewed or are not significantly skewed.

4.2. CAPM Analysis

For the CAPM statistics, the Sharpe ratio that measures the excess return per unit of risk is the conventional formula for stock evaluation where the risk is determined by the standard deviation. The higher the Sharpe ratio, the better the portfolio return is relative to risk, or the larger the excess return is per unit of risk in a portfolio. All Sharpe ratios are negative, except for C23, T17, and T33, while the Sharpe ratio of T17 is higher than all the eight selected warrants in China. Nearly all the Sharpe ratios are negative, which implies that, in general, investors are losing money in both Chinese and Taiwanese warrant markets.

The Sharpe ratio of T17 is higher than all the eight selected warrants in China. In general, the Sharpe ratio for warrants for Taiwan is higher than those in China, which indicates that Taiwanese warrants perform better than their counterparts in China. It can be concluded that, in general, the Sharpe ratio for warrants for Taiwan is more appealing, while that from China is too negative. This could make investors avoid investing in China warrants which, in turn, could lead to the closure of its market.

Similar to the Sharpe ratio, all Jensen indexes are also negative, except for T17 and T33. T33 has the highest Jensen index among all the warrants. A higher Jensen index suggests a higher level of return given the level of risk (systematic or market) on the investment. A low Jensen index, such as a negative number, indicates an inferior performance given the level of risk. The empirical findings that the values of the Jensen index for most warrants from both China and Taiwan are negative imply a poor performance of both warrant markets during the sample period. It is interesting that T33 is higher than all eight selected warrants in China. Nevertheless, the Jensen index of T1 (the Taiwan warrant with minimum Jensen index) is also larger than its counterpart in China, namely C14.

In general, the Jensen index for warrants for Taiwan is higher than in China, inferring that Taiwanese warrants perform better than Chinese warrants. Thus, we can conclude that, in general, the Jensen index for warrants for Taiwan is more appealing, while that from China is too negative. This could make investors avoid investing in Chinese warrants which, in turn, could lead to the closure of the market in China.

The Treynor ratio expresses the relationship of excess fund return, with the beta lying along the security market line taking account of the systematic risk or market volatility as its measure of risk, instead of the standard deviation, as in the Sharpe ratio. The Treynor index for China ranges from -61 to +20, indicating that Chinese warrants are very volatile. The higher volatility in the China warrants could make investors avoid investing in China warrants which, in turn, could lead to the closure of the market.

In summary, CAPM analysis demonstrates that Taiwanese warrants perform better than Chinese warrants in terms of the Sharpe ratio and Jensen index. In addition, the Chinese warrant market is volatile for investors according to the Treynor ratio. Therefore, China closed its warrant market after the end of the share-split reform, which expired completely in 2010. In the future, China might rethink reopening its warrant market and learning from mature-covered warrant markets, such as Taiwan, as to how it might be possible to inhibit excess speculation and to educate warrant investors.

4.3. SD Analysis

Table 3 reports the SD results based on the modified DD statistics. From the SD results, most of the Chinese warrants stochastically dominate Taiwanese warrants at the second and third orders, implying that risk averters prefer investing in Chinese warrants to Taiwanese warrants. However, there are still some pairs of Chinese and Taiwanese warrants that do not dominate each other. For example, for the pair of minimum mean return, C14 does not dominate T13 for any order. For the comparison among the maximum Jensen ratio, there is no SD between C14 and T33 for any order.

Table 3. SD Results for selected pairwise comparison.

Pairwise Comparison	Ascending SD
C14-T13	No SD
C23-T33	C $\succ_{2,3}$ T
C44-T17	C $\succ_{2,3}$ T
C47-T12	C $\succ_{2,3}$ T
C06-T15	C $\succ_{2,3}$ T
C23-T17	C $\succ_{2,3}$ T
C47-T17	No SD
C52-T26	C $\succ_{2,3}$ T
C55-T25	C $\succ_{2,3}$ T
C12-T17	C $\succ_{2,3}$ T
C23-T01	C $\succ_{2,3}$ T
C14-T33	No SD

Notes: C14-T13 is the pair of mean min, C23-T33 is the pair of mean max; C44-T17 is the pair of s.d min, C47-T12 is the pair of s.d max; C06-T15 is the pair of Sharpe ratio min, C23-T17 is the pair of Sharpe ratio max; C47-T17 is the pair of beta min, C52-T26 is the pair of beta max; C55-T25 is the pair of Treynor ratio min, C12-T17 is the pair of Treynor ratio max; C23-T01 is the pair of Jensen ratio min, C14-T33 is the pair of Jensen ratio max.

In order to illustrate the SD relationship better, we plot the distributions of the excess returns, F and G, for Chinese and Taiwanese warrants, and the corresponding DD statistics for the pair of C23 and T33, as shown in Figure 1. From Figure 1, we find that F is below G for some negative returns, while G is below F for some positive returns, implying that the excess return in the Chinese warrant is preferred in the negative domain, while the excess return in the Taiwanese warrant is preferred in the positive domain. In addition, it is clear that the first-order DD statistic (T1) is negative when the returns are negative, and becomes positive when the returns are positive. These results imply that the excess return in the Chinese warrant is preferred in the negative return and the excess return in the Taiwanese warrant is preferred in the positive return. It is also worth noting that both the second- and third-order DD statistics (T2 and T3) are negative, with some regions being significant.

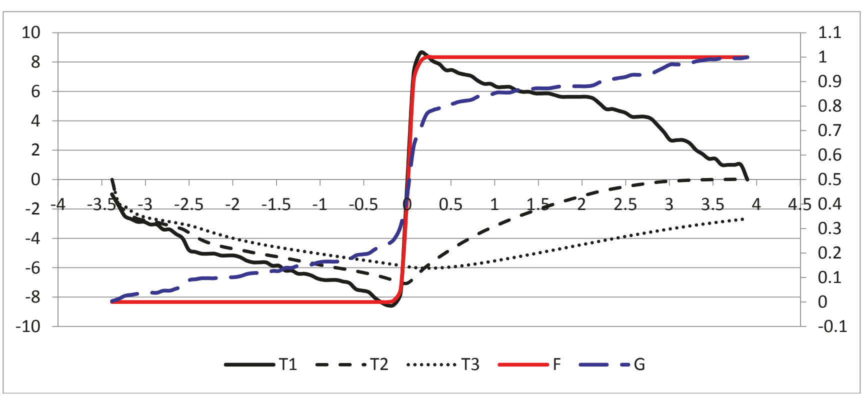

Figure 1. Ascending DD statistics distribution for C23-T33. Note: T_j is the test statistic defined in (3) for j = 1, 2 and 3. F and G are the CDFs of the excess warrant returns for C23 and T33, respectively.

In general, all investors with increasing utility functions prefer the negative excess return in Chinese warrants and prefer the positive excess return in Taiwanese warrants. For these reasons, there is no first-order SD between Chinese and Taiwanese warrants, and no arbitrage opportunity (see Guo et al. [71] and the references listed therein for further information) in the markets for Chinese and Taiwanese warrants.

However, Chinese warrants dominate Taiwanese warrants at the second and third orders, implying that second- and third-order risk averters prefer to invest in China as compared with Taiwan. This implies that the markets for Chinese and Taiwanese warrants are not efficient if investors are risk averters (see Qiao et al. [21], Clark et al. [69], and the references cited therein, for further information).

It can be concluded that Chinese warrants could be underpriced, so that it is more difficult for Chinese warrant issuers to make profits. This could be one of the main reasons why the market for Chinese warrants is not sustainable. Another reason that China presently has no warrant market is that the warrants issued by companies were used for compensation in the share reform from 2004 to 2008, and they expired in 1 to 2 years. China closed its warrants market because of the gradual expiration of reform-related warrants, excessive speculation, and lack of understanding of the warrants market by its participants.

4.4. Volume Analysis

We further examine the market activities between the Chinese and Taiwanese warrants. To do so, we analyse the daily trading volumes of Chinese and Taiwanese warrants that were selected in Section 3.1. In order to make the comparison practical, we convert both currencies in USD and exhibit the daily trading dollar value when the prices are in USD. These results are presented in Table 4 for Chinese and Taiwanese warrants.

Table 4. Summary statistics of trading volume (in USD) for selected Chinese and Taiwanese warrants.

Warrant Code	Mean	Std. Dev.	Skewness	Kurtosis	JB
C06	96,150.9500	73,283.1200	2.1843	10.0706	690.7704
C12	173,603.0000	324,388.6000	3.4949	17.0166	4926.9010
C14	46,306.6400	44,987.5000	1.8837	7.1179	150.5576
C23	55,458.4900	46,573.7300	1.9508	8.4068	440.8489
C44	214,101.4000	178,940.0000	1.9563	7.5217	718.0678
C47	40,012.9900	40,078.6000	2.3406	10.4683	760.7066
C52	59,475.6700	51,874.5500	2.4878	10.7968	848.3305
C55	48,996.5800	60,061.5300	3.2302	16.5166	2216.2940
T1	15.3537	103.6143	10.5616	113.3553	61,544.3700
T12	18.4588	72.0669	9.8558	105.4079	57,098.5700
T13	25.7770	127.7570	10.4158	111.5797	60,098.8800
T15	11.4235	75.4091	13.2409	178.1744	240,636.5000
T17	0.1405	0.4666	4.8718	29.5315	4194.0060
T25	37.7894	74.4648	2.3908	8.2631	265.4654
T26	79.8744	149.2158	7.2949	69.3507	24,230.2100
T33	107.3186	117.9072	2.8163	14.5546	839.9515

From Table 4, we find that the average daily trading volume of most Chinese warrants is of order 105, while that of most Taiwanese warrants are of the order 102. The average daily trading volume of individual Chinese warrants is 103 times greater than that of individual Taiwanese warrants. Thus, it can be concluded that the Chinese warrant market is much more active than its Taiwanese counterpart.

In China, there were only 55 warrants traded in the market, but the trading volume was once ranked the highest in the world. In Taiwan, the warrant market has experienced rises and falls, but there are currently more than 10 thousand warrants issued every year. Although the total trading volumes of warrants in China and Taiwan are the highest in the world, China had far fewer warrants than Taiwan. Thus, it is not surprising that the trading volume for "each warrant" in China is much greater than in Taiwan. Investors in China prefer warrants to stocks because of trading rules and transaction costs, as mentioned in Section 1. Thus, they are keen to trade fewer warrants available in the market, and hope to chase for the prices of warrants (Xiong and Yu, [1]). In other words, the Chinese warrant market is predominantly speculative, which can cause a greater number of trades.

5. Concluding Remarks

Academics, practitioners, and policy makers are interested in examining why the warrant market in China is not sustainable. In order to study this phenomenon, Fung et al. [18] point out the issues of over-speculation and lack of recognition of participants. Liao and Chen [4] determine that the expiration of call warrants have a significantly negative price effect during the last few days of the sample period. Xiong and Yu [1] find that the daily trading volume of many warrants is more than 3 times of the issuance volume.

Chang et al. [15] discovered that the market price of warrants is far higher than the prices from Black–Scholes models using historical volatilities. Liao et al. [14] find that 121.64 million shares of warrants were either exercised with an immediate loss, or failed to be exercised. Powers and Xiao [16] show that put warrant market prices averaged 1.2 yuan more than model-generated prices (over-priced), while call warrant prices averaged 1.9 yuan less (under-priced).

In this paper, we bridge a gap in the literature by using moment analysis, CAPM statistics, SD test, and volume analysis to examine investor preferences towards warrants between China and Taiwan, and investigate why the market for warrants in China is not sustainable while the market for Taiwanese warrants is succeeding.

Using moment analysis, we find that the mean excess returns are, in general, higher for Taiwanese warrants, while most of the mean excess returns for Chinese warrants are negative. In addition, most of the Chinese warrants have more significant and negative skewness, and significant and greater kurtosis than Taiwanese warrants. This information implies that buying Chinese warrants has a much higher chance for sustaining losses than Taiwanese warrants. This could make investors avoid investing in Chinese warrants which, in turn, could lead to the closure of the market for Chinese warrants.

Using CAPM analysis, the Sharpe ratio for warrants for Taiwan is higher than for China, and the Jensen index for warrants in Taiwan is higher than in China, inferring that Taiwan warrants perform better than China warrants. In general, both the Sharpe ratio and Jensen index for warrants for Taiwan are more attractive, while those for China are too negative. This could make investors avoid investing in Chinese warrants which, in turn, could lead to the closure of the market for Chinese warrants. On the other hand, the Treynor index for Chinese warrants shows that they are very volatile which, in turn, could also lead to the closure of the market of Chinese warrants.

In summary, CAPM analysis demonstrates that Taiwanese warrants perform better than Chinese warrants in terms of the Sharpe ratio and Jensen index. In addition, the Chinese warrant market is volatile for investors, according to the Treynor ratio. Therefore, China closed its warrant market after the end of the share-split reform and the warrants expired completely in 2010. In the future, China might think about reopening its warrant market and learning from mature-covered warrant markets, such as Taiwan's, how to inhibit excess speculation and to educate warrant investors.

Using SD analysis, there are no arbitrage opportunities between the Chinese and Taiwanese warrant markets, but the warrant markets in China and Taiwan are not efficient because the Chinese warrant market dominates Taiwan at the second and third orders, implying that second-order and third-order risk averters prefer to invest in China compared with Taiwan. This implies that the warrant issuers prefer to issue Taiwanese warrants than Chinese warrants, which could be another reason why the warrant market in China is not sustainable.

Based on volume analysis, the empirical findings show that the average daily trading volume of individual Chinese warrants is 103 times higher than individual Taiwanese warrants, so that the Chinese warrant market is much more active than its counterpart in Taiwan. This would seem to suggest that there are more speculative activities in the China warrant market than the Taiwanese warrant market which, in turn, could lead to China's decision to close its warrant market.

Another reason for China presently having no warrant market is that warrants issued by companies were used for compensation in the share reform during the period of 2004 to 2008, which expired in 1–2 years. China closed the warrant market because of the gradual expiration of reform-related warrants, excessive speculation, and lack of understanding of the warrants market by its participants.

The findings in the paper are important for investors for their investment decisions regarding Taiwanese and Chinese warrants, challenging for academics in modelling Taiwanese and Chinese warrants, and useful for policy makers for their policy making related to Taiwanese warrants and Chinese warrants. In the future, China might rethink reopening its warrant market and learning from mature-covered warrant markets such as Taiwan how to inhibit excess speculation and to educate warrant investors.

The paper investigated the preferences of risk averters to invest in warrants between China and Taiwan. Extensions include using other tools to compare the preferences for risk averters to invest in warrants between China and Taiwan, as well as investigate the preferences of other types of investors (see Chang et al. [72–76] for further information).

We note that this paper is studying whether the warrant market is sustainable. There are many other studies investigating whether other markets are sustainable, see, for example, Moslehpour, et al. [77] and Li, et al. [78,79]. We also note that there could be many directions for further studies. One of them is to study the preference of other types investors, for example, investors with S-shaped and reversed S-shaped utility functions, see, for example, Wong and Chan [80] and the references therein for more information.

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Financial Credit Risk Evaluation Based on Core Enterprise Supply Chains

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Abstract: Supply chain finance has broken through traditional credit modes and advanced rapidly as a creative financial business discipline. Core enterprises have played a critical role in the credit enhancement of supply chain finance. Through the analysis of core enterprise credit risks in supply chain finance, by means of a 'fuzzy analytical hierarchy process' (FAHP), the paper constructs a supply chain financial credit risk evaluation system, making quantitative measurements and evaluation of core enterprise credit risk. This enables enterprises to take measures to control credit risk, thereby promoting the healthy development of supply chain finance. The examination of core enterprise supply chains suggests that a unified information file should be collected based on the core enterprise, including the operating conditions, asset status, industry status, credit record, effective information to the database, collecting related data upstream and downstream of the archives around the core enterprise, developing a data information system, electronic data information, and updating the database accurately using the latest information that might be available. Moreover, supply chain finance and modern information technology should be integrated to establish the sharing of information resources and realize the exchange of information flows, capital flows, and logistics between banks. This should reduce a variety of risks and improve the efficiency and effectiveness of supply chain finance.

Keywords: supply chain finance; core enterprises; financial credit risk evaluation; fuzzy analytical hierarchy process (FAHP)

1. Introduction

Small and medium-sized enterprises (SMEs) have generally played the most significant role in the development of the national and provincial economies in China. SMEs have made great strides that have accounted for over 98% of all enterprises, contributed more than 60% of growth in GDP and foreign trade for economic development nationwide, provided over 80% of job opportunities, and more than 50% of business revenues. Although SMEs have experienced an overall performance that would be characterized as excellent and have an irreplaceable role in promoting the national economy, their financial environment has been, and remains, susceptible and sensitive to changing financial conditions at all levels.

Overall, SMEs face greater financial constraints than do larger firms. There are measures that are intended to alleviate the financial constraints of SMEs, such as leasing and factoring that are helpful in facilitating access to finance in the absence of well-developed financial institutions. Numerous studies have argued that SMEs are financially more constrained than large firms.

SMEs are major players in the economy, such that the current financial market failure is an obstacle to their expansion and growth. For this reason, SMEs need administrative and financial support from governments at all levels. However, despite the growing interest in subsidizing SMEs, there are concerns about whether these measures are helpful and sufficient. According to statistics from the People's Bank of China, SMEs have obtained bank loans that account for 16% of the loans of financial institutions, and bank supporting loans to SMEs lie in the range 30–40%. Moreover, virtually 80% of SMEs are experiencing capital circulation problems.

As SMEs have not received financial support relative to the contribution they have made to the economy, their financial problems have become a barrier that affects the sustainable development of SMEs. Given this background, the financial supply chain enters as an important participant to the financial system, with associated financial credit risks.

The remainder of the paper is as follows. Section 2 gives a literature review, including the definition of supply chain finance, credit risk evaluation of supply chain finance, and risk control for supply chain finance. The theory of supply chain financial core enterprise risks is discussed in Section 3, including credit, guarantee, and operational risk. Section 4 presents the fuzzy analytical hierarchy process (FAHP) framework, including the fuzzy judgment matrix and a check for its consistency, the weight vector, and composite weight vector. The empirical analysis is evaluated in Section 5, including a discussion of core enterprises, an evaluation system of the core enterprise credit risk, and model construction and solution. Some concluding remarks are presented in Section 6.

2. Literature Review

International research on supply chain finance started before similar developments in China, the mode of operation is more mature, and the achievements are relatively advanced. Regarding relationship between supply chain and financing, Berger et al. (2006) [1] advanced the conceptual framework for the development and financing of global small and medium-sized enterprises and established the idea of supply chain finance. Klapper (2005) [2] analyzed the principles underlying the inventory financing model, and the functions that small and medium-sized enterprises had adopted in the supply chain.

The development of China's supply chain finance began around 2000. In 2005, the financing mode of "1 plus N" implemented by the Shenzhen Development Bank (since renamed the Ping An Bank) offered a $250 billion credit line, making 25% profit, with the non-performing loans accounting for 0.57% of all supply chain finance.

In recent years, supply chain finance has been developing rapidly. Statistics show that by the end of 2015, 60% of SMEs had chosen supply chain finance to alleviate the shortage of business liquidity. However, as an innovative financing method, supply chain finance also has certain risks, such as the financing of small and medium-sized enterprise core banks, whereby one party's credit problems can lead to the failure of supply chain financing and the loss of other participants. While SMEs are undoubtedly the engine of economic growth, their speed of growth will be dampened by market imperfections and institutional weaknesses (for further details, see [3] Beck and Demirguc-Kunt (2006)).

In [4] Shi et al. (2014), the fuzzy analytical hierarchy process was applied for risk evaluation in model building of logistics financial business for banks. The information asymmetry between banks and enterprises and imperfect mechanism bring some risk to banks carrying out the logistics and financial business. Using logistics financial risk indicators, the risk evaluation index system of logistics finance from the pledge risk, financing enterprise credit risk, logistics enterprise risk, and regulatory risk, the risk evaluation model of logistics financial business for the bank is established by using fuzzy mathematics theory and an analytic hierarchy process.

Further to the above, [5] Shi et al. (2015) evaluated the credit risk of online supply chain finance based on third-party B2B e-commerce platform for China. The system applies the multi-level gray evaluation model based on the Theil index to make a comprehensive evaluation on the credit of the loan enterprise and tests the model's feasibility through the analyses of a numerical example. The evaluation model overcomes the subjectivity of weight distribution to index and presents the degree of the indices on each hierarchy distinctly so as to enable banks to take risk control specifically in operation.

Through the analysis of core enterprise credit risks in supply chain finance, by means of a 'fuzzy analytical hierarchy process' (FAHP), the paper constructs a supply chain financial credit risk evaluation system. This paper extends the work of the two papers just mentioned by discussing the fuzzy judgment matrix, developing a fuzzy Judgment matrix consistency check, weight vector of index layer C, weight vector of index layer C to criterion layer B, and composite weight vectors. The paper also provides a detailed empirical example that highlights the novelty of the model construction and solution. These are the primary and novel purposes of the paper.

2.1. Definition of Supply Chain Finance

The definition of supply chain finance will cover significant contributions from 2005 until the present. According to the definition of supply chain finance (SCF) in [6] Hofmann (2005), it relies on two or more organizations in the supply chain to cooperate on financial resources to create extra values jointly, although these organizations remain independent. Pfohl and Gomm (2009) [7] argued that SCF could raise the value of participating firms in the supply chain, in addition to the value of leading firms in the supply chain.

Several years later, according to [8] Gupta and Dutta (2011), with increasingly fierce competition, it becomes more important to improve the efficiency of working capital by using cash that is trapped in the financial supply chain (FSC). Mathis and Cavinato (2010) [9] argued that banks should play a more active role in the FSC to integrate the resources in the chain. Silvestro and Lustrato (2014) [10] showed that banks are key players that can offer alternative supply chain solutions in the FSC.

More recently, in a related development, [11] Blackman et al. (2013) proposed a formal definition that a 'financial supply chain' is the network of organizations and banks that coordinate the flow of financial transactions through shared information systems to facilitate a product supply chain between trading partners.

SCF can be defined in many ways, depending on perspective and orientation. The analysis of the different definitions and conceptual contributions highlights two major perspectives on SCF, which can be identified as 'financial-oriented' from which a further 'buyer-driven perspective' can be identified) and 'supply chain-oriented'. The financial perspective interprets SCF as a set of (innovative) financial solutions (for further details, see [12] Caniato et al., 2016).

SCF has increasingly become a hot topic in supply chain management and a growing product category of financial institutions (FIs). In China, SCF is experiencing a rapid development stage, and numerous FIs have begun to focus on developing and designing new SCF services and products to solve the financing issues facing SMEs. SCF is a channel for financing, which manages, plans, and controls all cash flows across supply chain members to improve the turnover efficiency of working capital. In SCF, SMEs obtain loans with looser constraints from banks through expanded credit lines. Core enterprises (CEs) alleviate the pressure of funding, and financial intermediaries dramatically increase their incomes.

More specifically, SCF significantly decreases the credit risk of SMEs for FIs. Nevertheless, SCF cannot completely eliminate credit risk, which continues to be one of the major threats to FIs. Moreover, SCF has been promoted for almost 10 years and has experienced slow development in China because there is not as yet an appropriate SME credit risk evaluation index system, or an outstanding prediction model, which hinders SCF (for further details, see [13] Zhu et al., 2016)).

SCF is concerned with the capital flows within a supply chain, an area that has often been neglected in the past. Nevertheless, SCF does have an impact on a firm's capability for adopting sustainable supply chain management (SCM) practices (for further details, see [14] Liu et al. (2015)).

2.2. Credit Risk Evaluation of Supply Chain Finance

In China, SMEs are the main applicants of SCF, so that banks suffer from credit risk in SCF when the SMEs cannot honor agreements and contracts. It is generally agreed that structuring the SME credit risk evaluation index system is the greatest and most critical challenge to bank management of SCF, and that it is fundamental to credit loan decision making. A good credit risk evaluation index system can guarantee profitability and stability of a FI, whereas a poor system can potentially lead to significant losses (for further details, see [13] Zhu et al., 2016).

In previous studies, experts and scholars paid greater attention to the credit risk of SMEs, while neglecting the credit risk of core enterprises, which is one of the main financial entities of the supply chain. In fact, the core enterprises' credit risk is the key to influence the effective implementation of supply chain finance.

Feldmann and Müller (2003) [15] emphasized the role of asymmetric information held by supply chain partners who are opportunistically behaved. Silvestro and Lustrato (2014) [10] argued that the factors that could affect the risk of SCF include supply chain co-ordination, cooperation, and information sharing.

In a much earlier contribution, [16] Berger and Udell (1998) found that small firms have limited access to external financing, and were more tightly constrained in their operations, both in developing and developed countries. Galindo and Schiantarelli (2003) [17] drew the same conclusion for countries in Latin America.

Schiffer and Weder (2001) [18] found that small firms consistently face greater growth obstacles than do large firms, which implies that size is one of the most reliable factors for financing obstacles confronting firms, except for age and ownership of firms (for further details, see [19] Beck et al., 2006).

Song and Zipkin (2009) [20] analyzed the methods for determining the quality of goods in the pawn financing process. Moreover, an investigation by [21] Wuttke et al. (2013) indicated that it is better for the supply chain enterprises of SMEs to adopt a "pre–shipment" financing model in preference to a "post-shipment" funding model. Furthermore, both corporations and banks have shown great interest in using SCF techniques to ease their tensions in the supply chain, and also in making large corporations shorten the payment periods for their key suppliers (for further details, see [22] Randall et al, 2009)).

Very recently, [13] Zhu et al. (2016) proposed an SME credit risk evaluation index system specifically designed for SCF. This system is used to evaluate the credit risks from different points of view, which not only consist of financial and non-financial conditions of SMEs, but also contain the financial and non-financial conditions of CEs, the operational status of the entire supply chain, and the transactional relationship between SMEs and CEs (for further details, see [13] Zhu et al., 2016)).

Therefore, measuring and evaluating the credit level of core enterprises, and controlling the credit risk of core enterprises, are the keys to using supply chain finance in an efficient manner.

2.3. Risk Control for Supply Chain Finance

As mentioned above, there has been substantial and informative research on supply chain finance for SMEs. Nevertheless, there remain some limitations. There has been little research on collaborative supply chain finance for SMEs, and the research has not necessarily been systematic.

In 1931, the British Financial Industry Council established the Macmillan Committee—officially known as the [23] Committee on Finance and Industry (1931)—and presented the Macmillan Report after investigating the British financial industry, and industry and commerce. The report noted that, in the UK financial system, there is a gap between SMEs and financial institutions (for further details, see [24] Stamp (1931)). To date, no research has considered a systematic analysis for the overall optimization of supply chain finance for SMEs in attempting to solve the "Macmillan gap".

Lee and Rhee (2011) [25] demonstrated that, through the coordination and establishment of commercial credit among SMEs, the results of risk control for supply chain finance of SMEs are better than those of financial risk control by financial institutions for the individual companies.

The apparent ability of some supply chains to recover from inevitable risk events more effectively than do others has recently triggered a debate about supply chain resilience (SCRES). While SCRM focuses on the identification and management of risks for the supply chain in order to reduce its vulnerability, SCRES aims at developing the adaptive capability to prepare for unexpected and contingent events, to respond to disruptions, and subsequently recover from them (for further details, see [26] Jüttner and Maklan, 2011)).

3. Theory of Supply Chain Financial Core Enterprise Risks

In supply chain finance, core enterprises are the exchange center of capital flows, information flows, and logistics, and play an important role in the supply chain financing. The risks can vary, including three major risks—namely credit, guarantee, and operational risks—which are discussed below.

3.1. Credit Risk

Core enterprises play an important role in supply chain finance, and play key roles in connecting the supply chain capital flows, information flows and logistics. Banks are based on the core enterprise's strength and credit guarantee and select the upstream and downstream enterprises to perform credit activities. Therefore, the core enterprise conditions and development prospects determine the smooth operation of the supply chain. The credit status of core business problems will inevitably spread to the supply chain with the upstream and downstream enterprises, thereby affecting the overall supply chain finance security and operational efficiency, leading to supply chain financing failure.

Core enterprise credit risk manifests itself in two respects. The core enterprise can undertake the entire supply chain finance guarantee function when they are experiencing poor management themselves. Moreover, the core enterprise may be confronted with a credit crisis due to bonding credit which exceeds its credit capacity, resulting in financing failure. As the core enterprise development prospects are not encouraging, their power is diminished.

A core enterprise may conceal their real transaction records with different parties in the supply chain, which leads to false financing. This can affect their actual performance, so that they will not be able to satisfy the conditions of the agreement with the bank, in which case the SMEs financing will eventually fail.

3.2. Guarantee Risk

For the core enterprise, the so-called guarantee risk arises in financing when SMEs break a contract. When SMEs cannot continue payments of bank loans, the core enterprise, as a guarantor of SMEs, has to bear the associated bank losses. In supply chain finance, guarantees by the core enterprise of the credit situation of SMEs leads to a greater strength of SMEs, and the possibility of reducing the risk of banks in lending money to SMEs through promoting enterprise production and business development. If the core enterprise intends to give credit to SMEs, the core enterprise should be careful in selecting SMEs in the supply chain that are financially strong so as to reduce guarantee risk.

3.3. Operational Risk

In the process of supply chain financing, many of the required steps need to be confirmed manually, so operational risk needs to be accommodated. The operation of the three main financing risk are also different. For example, the operational risk of accounts receivable financing mode focuses primarily on the management of accounts receivable.

The existence of sales discounts will lead to errors when the accounts receivable are checked. Moreover, given the fact that receivables financing is a repeatedly regular procedure, the payments and actual deviations occur when the core enterprises are confirming such payments. In addition, the accounts receivable settlements involve enterprises and many settlement accounts. As the procedures for repayment can be complicated, especially when the methods for the accounts receivable transfer payments change, operational errors are more prone to occur, thereby leading to greater operational risk.

Overall, the greatest influence on the supply chain of the three different types of risks mentioned above is financial credit risk. As the main participant in the supply chain, the core enterprise credit level has a significant influence on the success in financing. In order to reduce the financial risks of the supply chain, the effective control of core enterprise credit risk is fundamental.

4. Fuzzy Analytical Hierarchy Process (FAHP) Framework

Saaty (1990) [27] introduced a multi-factors decision making approach, in which factors are arranged in a hierarchical structure. In order to apply the FAHP method, it is necessary to construct a hierarchy that expresses the relative values of a set of attributes. Decision makers evaluate the relative importance of the attributes in each level based on the FAHP scale which, in turn, is used to direct them to express their preferences between each pairwise comparison. Then the decision makers are required to determine whether the element is of equal importance, somewhat more important, much more important, very much more important, or absolutely important, relative to another element.

These important intensities are, respectively, converted to numeral values in the FAHP scale as 1, 3, 5, 7, 9 and 2, 4, 6, 8, as the intermediate values (see Table 1). By using this scale, the qualitative judgments of evaluators are converted into quantitative values, which enable construction of a pairwise comparison matrix. The pairwise comparison matrix is made for all elements to be considered in the construct hierarchy. The results from these comparisons are used to calculate a list of admittedly arbitrary though reasonable weights, and importance of the factors (eigenvectors) based on the rapid application development (RAD) method. Arbitrary means that mathematical optimization for determining the weights was not used as it would have required a mathematical model to have been imposed on the structure of the model.

Table 1. FAHP Scale.

Intensity of AHP Scale	Linguistic Variable	Positive Value	Positively Reciprocal Value
1	Same importance	(1, 1, 1)	(1, 1, 1)
3	Weakly more important	(2, 3, 4)	(1/4, 1/3, 1/2)
5	Fairly more important	(4, 5, 6)	(1/6, 1/5, 1/4)
7	Strongly more important	(6, 7, 8)	(1/8, 1/7, 1/6)
9	Absolutely more important	(8, 9, 10)	(1/10, 1/9, 1/8)
2, 4,6,8	Intermediate values		

4.1. Fuzzy Judgment Matrix

Fuzzy judgment matrix can be used to compare the importance of different indicators. The level of importance of two elements are assumed to be incorporated into an index labelled as T, and the hierarchical elements, $a_1, \ldots, a_n$ represent the existing fuzzy relation, all of which constitute a fuzzy matrix, as given below:

$$\begin{array}{c|cccc} T & a_1 & a_2 & \cdots & a_n \\ a_1 & r_{11} & r_{12} & \cdots & r_{1n} \\ a_2 & r_{21} & r_{22} & \cdots & r_{2n} \\ & & & & \\ a_n & r_{n1} & r_{n2} & \cdots & r_{nn} \end{array} \tag{1}$$

In the fuzzy T index matrix, r_{ij} denotes a judgment value which represents the extent to which a_i is much more important than a_j, when the two elements a_i and a_j are compared.

Pairwise comparisons among the main factors, sub-factors, and alternatives are produced based on the typical nine-point scale combined with fuzzy numbers. The next step is to calculate the admittedly arbitrary priority weights of factors, sub-factors, and alternatives by adopting the FAHP approach.

The idea of calculating the priority weights of attributes is based on the pairwise comparisons given in the questionnaire (for further details, see Appendix A). In doing so, a set of comparison questions are proposed in order to ask the experts their opinions. The higher the evaluation is, the greater the importance of a factor will be.

Corresponding to three levels of the hierarchical model, the experts first evaluate the four main factors in the second level with respect to the overall goal. In the third level, pairwise comparisons of alternatives are made with respect to the overall goal.

In order to obtain the quantitative value of the compared importance between each two indicators, fuzzy numerical values from 1 to 9 are employed, as shown in Table 1. With such comparisons between each two factors, the fuzzy judgment matrix can be constructed.

4.2. Fuzzy Judgment Matrix Consistency Check

A consistency check is the first condition for calculating the weights. Only if the consistency meets the requirements can the model be solved. A relatively simple judgment method is based on the following formula.

$$\mathrm{CI}(\mathrm{A},\mathrm{W}) = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\left|a_{ij} - \omega_{ij}\right| \tag{2}$$

The acceptable condition for the consistency judgment is $\mathrm{CI}(\mathrm{A},\mathrm{W}) \leq \alpha$, where the implication of α is the attitude of the decision maker. The higher is the consistency of the fuzzy judgment matrix required by the decision maker, the smaller will be the value of α. The value of α is most suitable when it is set to 0.01.

4.3. Weight Vector of Criterion Layer B

The determination of the weight vector is the key to the fuzzy judgment matrix which can be obtained after sorting out the results of the questionnaire given by the experts. The formula given in Equation (3) is used to solve the weight vector for each criterion layer. The weight given to each expert is multiplied by the weight vector, and the weight vector of the elements at the B layer, such that $\omega_B = (\omega_1, \ldots, \omega_n)$, can be obtained as

$$\omega_i = \frac{\sum\limits_{j=1}^{n} a_{ij} + 1 - \frac{n}{2}}{n} \text{ for any } \mathrm{i} = 1, 2, \ldots, \mathrm{n}. \tag{3}$$

4.4. Weight Vector of Index Layer C to Criterion Layer B

Each decision-making expert takes the B layer elements as the criterion, and gives the fuzzy judgment matrix, which is obtained by the C layer elements, compares two fuzzy judgment matrix, by using the same method, and thereby obtains the weight vector of each element of the C layer.

4.5. Composite Weight Vector

After calculating the priority weight vectors of the B and C layers, the following formula in Equation (4)

$$\omega_j = \sum_{i=1}^{n} w_i w_j \tag{4}$$

This equation is used to compute the composite weight vector and the priority weight vector of the different indexes to obtain the credit risk. The key risk factors can then be identified. In the formula, ω_j is the index values of no. j element and w_i w_i is the weight vector. No. i criterion layer, w_{ij} is the weight vector of the no. i criterion layer of the no. j index value.

5. Empirical Analysis

5.1. Introduction to Core Enterprises

The Wuhan Iron and Steel Group is affiliated to the state-owned SASAC important backbone enterprises, has a good credit rating, and substantial financial strength. It is among the core enterprises in the supply chain finance. The Wuhan Iron and Steel Group is in the production stage of the three stages of product supply, production, and sales.

The upstream enterprises act primarily as steel materials suppliers, which are responsible for the mining of steel. The Wuhan Iron and Steel Group has applied to various banks for financial loans by means of the receivables documents in the financing process.

Downstream enterprises are mainly steel dealers, which are responsible for the sales of steel. During the financing process, they select the financing mode of prepayment to purchase and apply for loans based on sales contracts.

The China Industrial Bank (CIB) has been cooperating with the Wuhan Iron and Steel Group in the supply chain finance since 2002. Until December 2015, the China Industrial Bank had 53 credit lines among the upstream and downstream dealers of the Wuhan Iron and Steel Group, with a credit amount that exceeded RMB 1.536 billion. The non-performing loan ratio of the upstream and downstream enterprises is very low, almost close to zero, which is a successful case of the implementation of supply chain finance.

5.2. Evaluation System of the Core Enterprise Credit Risk

The core enterprise risk control is the most important factor in the supply chain risk. For this reason, the construction of the core enterprise credit risk system is very important. This paper constructs a layer analysis using four approaches toward risk, namely the core enterprise industry position, management perspective, asset status, and credit record.

5.2.1. Core Enterprise Industry Status (B1)

The achievement of inter-enterprise transactions not only relies on the quality of goods, but also the industry status as the focus of attention. In general, the core enterprise industry status has a significant effect on their business conditions. This paper selects the macroscopic environment and the development situation of the enterprises as the secondary index of industry status evaluation.

5.2.2. Core Enterprise Operations (B2)

Banks are more concerned about the operation of the core enterprise with guarantees. The reason is that the core enterprise needs to assume the guarantee obligation in case of default by the SMEs. If the core enterprises do not have high solvency, the banks will not be in a position to offer loans to the SMEs as they need to consider their own financial interests. The operating performance of the core enterprises is mainly reflected in the three indicators of profitability, operating capacity, and solvency. This paper selects these three indexes as the secondary indicators in the evaluation system.

5.2.3. Asset Status of the Core Enterprises (B3)

The main premise of bank loans is that the core enterprise provides security for SMEs, such that, when SMEs breach their contracts, the core enterprises will accept their responsibility for the guarantees, thereby compensating the banks and reducing bank losses. Therefore, the asset status of the core enterprise is also an important focus of bank inspections. In this way, the ability of the core enterprise to cash financial assets is stronger than that of the monetary funds, receivable accounts, and inventories. This paper will take the three items as the secondary index of the current asset status evaluation.

5.2.4. Core Enterprise Credit History (B4)

The key to the successful financing of SMEs is the core enterprise credit guarantees to be bundled together with SMEs to form the overall credit. However, if the credit situation of the core enterprise is poor, even if the SMEs and the core enterprise credit guarantees are bundled together, the bank will not make the loans accessible. This paper selects the credit rating and the previous performance, namely the credit history, as the secondary index.

The hierarchy of the evaluation system of core enterprise credit risk can constructed, as shown in Figure 1. It is divided into three levels, and arranged in descending order. The first level presents the overall goal, which is the risk evaluation of supply chain financial core enterprises (A) and is situated at the top of the hierarchy. In the second level, four major factors are inserted into the model, namely industry status (B1), operation condition (B2), asset state (B3), and credit record (B4). Each factor includes several sub-factors in the third level of the hierarchy.

The industry status factor is explained by two sub-factors, namely macro-environment (C1) and enterprise development (C2). The operation condition includes operation ability (C3), profitability (C4) and solvency (C5). The asset state consists of monetary fund (C6), accounts receivable (C7), and inventory (C8). The credit history includes enterprise credit rating (C9) and past performance (C10).

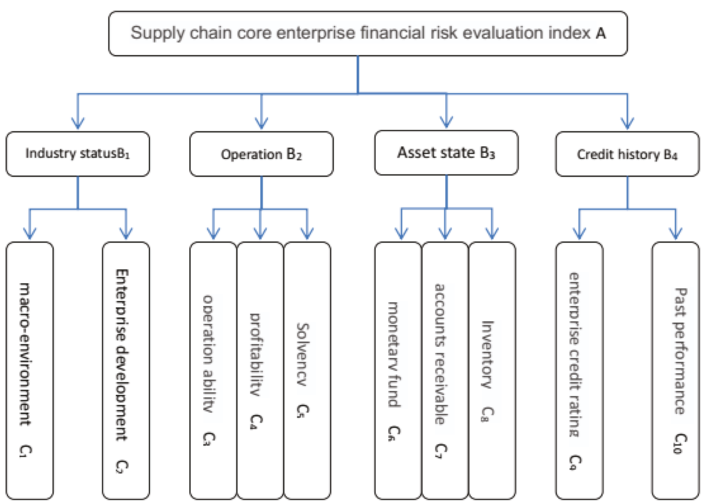

Figure 1. Core enterprise credit risk evaluation system hierarchical graph.

5.3. Model Construction and Solution

By using the risk evaluation system that was described above, including 4 risk categories and 10 risk factors, the risk identification model was constructed using a fuzzy analytic hierarchy process (FAHP), and the model was thereby solved. In this paper, the core enterprise employees are divided into four categories, namely managerial staff, senior engineers, middle-level employees, and general employees. The questionnaire is scored according to four types of employees (see below), with the fuzzy matrices given as B1, B2, B3, and B4.

The four types of employees are given as follows:

Managerial staff: They perform management functions, and direct or coordinate others to complete specific tasks in the organization. Their educational background is relatively good. They are familiar with the work flow of management and have a clearer business operation. Therefore, their assignment weights are 0.3. In this paper, a total of 50 managers were selected by the sampling method. After removing the highest and lowest scores, an average value was obtained.

Senior engineers: They are technical experts or technicians in the engineering field, play an irreplaceable role in the enterprise, and have strong working ability. In the enterprise work, they have a relatively professional technical background and authority, so their assignment weight is 0.3. In this paper, a total of 20 senior engineers were selected by the sampling method. After removing the highest and lowest scores, an average value was obtained.

Middle-level employees: They are managers at one or more intermediate levels between senior managers and grass-roots managers. Their main responsibilities are to implement major decisions made by senior managers, and to supervise and coordinate the work of grass-roots managers. Therefore, their work plays a connecting role. They are not as high as the headquarters management, and may only focus on part of the enterprise, so the assignment weight is 0.2. In this paper, a total of 50 middle-level employees were selected by the sampling method. After removing the highest and lowest scores, an average value was obtained.

General employees: Specifically engaged in various post work, and are at the forefront of staff, but their focus is their own post work. The overall perspective of the problem or risk is relatively small, so the assignment weight is 0.2. In this paper, a total of 50 employees were selected by the sampling method. After removing the highest and lowest scores, an average value was obtained.

These four categories of employees are given different weights, specifically managerial staff 0.3, senior engineers 0.3, middle-level staff 0.2, and general employees 0.2. Various types of employees on the B-layer elements are compared pairwise, and thereby obtain the fuzzy judgment matrix

$$B_1 = \begin{bmatrix} 0.5 & 0.7 & 0.6 & 0.4 \\ 0.3 & 0.5 & 0.4 & 0.4 \\ 0.4 & 0.6 & 0.5 & 0.3 \\ 0.6 & 0.6 & 0.7 & 0.5 \end{bmatrix} \tag{5}$$

$$B_2 = \begin{bmatrix} 0.5 & 0.8 & 0.7 & 0.6 \\ 0.2 & 0.5 & 0.5 & 0.4 \\ 0.3 & 0.5 & 0.5 & 0.3 \\ 0.4 & 0.6 & 0.7 & 0.5 \end{bmatrix} \tag{6}$$

$$B_3 = \begin{bmatrix} 0.5 & 0.7 & 0.8 & 0.6 \\ 0.3 & 0.5 & 0.6 & 0.4 \\ 0.2 & 0.4 & 0.5 & 0.3 \\ 0.4 & 0.6 & 0.7 & 0.5 \end{bmatrix} \tag{7}$$

$$B_4 = \begin{bmatrix} 0.5 & 0.8 & 0.9 & 0.5 \\ 0.2 & 0.5 & 0.7 & 0.2 \\ 0.1 & 0.3 & 0.5 & 0.3 \\ 0.5 & 0.8 & 0.7 & 0.5 \end{bmatrix} \tag{8}$$

The fuzzy judgment matrix is used to determine the fuzzy consistency of the four matrices, namely B1, B2, B3, B4, and the weight order vectors, that is, ωB1, ωB2, ωB3, ωB4, can be solved. By taking B1 as an example, the solution is given as

$$\begin{aligned} \omega_{B11} &= \tfrac{1}{4}\left(0.5+0.3+0.4+0.6+1-\tfrac{4}{2}\right) = 0.2 \\ \omega_{B12} &= \tfrac{1}{4}\left(0.7+0.5+0.6+0.6+1-\tfrac{4}{2}\right) = 0.35 \\ \omega_{B13} &= \tfrac{1}{4}\left(0.6+0.4+0.5+0.7+1-\tfrac{4}{2}\right) = 0.3 \\ \omega_{B14} &= \tfrac{1}{4}\left(0.4+0.4+0.3+0.5+1-\tfrac{4}{2}\right) = 0.15 \end{aligned} \tag{9}$$

Therefore:

$$\omega B1 = (0.2\ 0.35\ 0.3\ 0.15) \tag{10}$$

Similarly:

$$\begin{array}{c} \omega B2 = (0.1\ 0.35\ 0.35\ 0.2) \\ \omega B3 = (0.1\ 0.3\ 0.4\ 0.2) \\ \omega B4 = (0.075\ 0.35\ 0.45\ 0.125) \end{array} \tag{11}$$

Given the above, the weight of the four categories of employees can be added, and the B-level weight vector can be obtained as:

$$\begin{aligned} \omega_{B1} &= 0.3 \times 0.2 + 0.3 \times 0.1 + 0.2 \times 0.1 + 0.2 \times 0.075 = 0.125 \\ \omega_{B2} &= 0.3 \times 0.35 + 0.3 \times 0.35 + 0.2 \times 0.4 + 0.2 \times 0.35 = 0.34 \\ \omega_{B3} &= 0.3 \times 0.3 + 0.3 \times 0.35 + 0.2 \times 0.4 + 0.2 \times 0.45 = 0.365 \\ \omega_{B4} &= 0.3 \times 0.15 + 0.3 \times 0.2 + 0.2 \times 0.2 + 0.2 \times 0.125 = 0.17 \end{aligned} \tag{12}$$

As a result, the weight vector of the criterion layer to the target layer is $(0.125,\ 0.34,\ 0.36,\ 0.17)$. Given the construction, the total weight vector of the criterion layer to the target layer can be determined, as follows: the core enterprise asset weight is 0.365, and is ranked first; the operating weight is 0.33, which is ranked second; the credit record weight is 0.17, thereby being ranked third; the industry position weight is 0.125, and is ranked fourth.

The ranking constructed above shows that commercial banks are primarily concerned with the asset status of the core enterprise, followed by the core enterprise operation, then the credit record of the core enterprise, and finally the core enterprise industry status.

Under the premise of calculating the weight of the criterion layer, the weight value of each risk factor in the index layer can also be obtained. According to the questionnaire survey results of the 4 kinds of employees, the 10 risk factors in the index layer are compared with each other, the fuzzy judgment matrix is constructed, and the single ranking weight vector is obtained according to the judgment matrix.

In this paper, the weight vector of the criterion layer B to each element in the C layer is taken as an example. The fuzzy judgment matrix, $C1k(k = 1,\ 2,\ 3,\ 4)$, is constructed, as given in Appendix B.

The same method is used to obtain the weight vector, namely,

$$\begin{aligned} \omega_{C11} &= \tfrac{1}{10}\left(0.5 + 0.6 + 0.7 + 0.5 + 0.3 + 0.7 + 0.5 + 0.8 + 0.6 + 0.5 + 1 - \tfrac{10}{2}\right) = 0.17 \\ \omega_{C12} &= \tfrac{1}{10}\left(0.4 + 0.5 + 0.4 + 0.6 + 0.4 + 0.7 + 0.7 + 0.3 + 0.5 + 0.6 + 1 - \tfrac{10}{2}\right) = 0.11 \\ \omega_{C13} &= \tfrac{1}{10}\left(0.\ 3 + 0.6 + 0.5 + 0.4 + 0.7 + 0.5 + 0.4 + 0.2 + 0.5 + 0.4 + 1 - \tfrac{10}{2}\right) = 0.05 \\ \omega_{C14} &= \tfrac{1}{10}\left(0.5 + 0.4 + 0.6 + 0.5 + 0.3 + 0.2 + 0.8 + 0.6 + 0.7 + 0.5 + 1 - \tfrac{10}{2}\right) = 0.11 \\ \omega_{C15} &= \tfrac{1}{10}\left(0.7 + 0.6 + 0.3 + 0.7 + 0.5 + 0.5 + 0.8 + 0.1 + 0.5 + 0.7 + 1 - \tfrac{10}{2}\right) = 0.14 \\ \omega_{C16} &= \tfrac{1}{10}\left(0.3 + 0.3 + 0.5 + 0.8 + 0.5 + 0.5 + 0.4 + 0.7 + 0.2 + 0.5 + 1 - \tfrac{10}{2}\right) = 0.07 \\ \omega_{C17} &= \tfrac{1}{10}\left(0.5 + 0.3 + 0.6 + 0.2 + 0.2 + 0.6 + 0.5 + 0.7 + 0.8 + 0.6 + 1 - \tfrac{10}{2}\right) = 0.1 \\ \omega_{C18} &= \tfrac{1}{10}\left(0.2 + 0.7 + 0.8 + 0.4 + 0.9 + 0.8 + 0.3 + 0.5 + 0.3 + 0.5 + 1 - \tfrac{10}{2}\right) = 0.14 \\ \omega_{C19} &= \tfrac{1}{10}\left(0.4 + 0.5 + 0.5 + 0.3 + 0.3 + 0.3 + 0.2 + 0.7 + 0.5 + 0.5 + 1 - \tfrac{10}{2}\right) = 0.02 \\ \omega_{C10} &= \tfrac{1}{10}\left(0.5 + 0.4 + 0.6 + 0.5 + 0.3 + 0.5 + 0.4 + 0.5 + 0.5 + 0.5 + 1 - \tfrac{10}{2}\right) = 0.07 \end{aligned} \tag{13}$$

Therefore:

$$\omega C1 = (0.17\ 0.11\ 0.05\ 0.11\ 0.14\ 0.07\ 0.1\ 0.14\ 0.02\ 0.07) \tag{14}$$

Similarly:

$$\begin{aligned}\omega C2 &= (0.1\ 0.11\ 0.15\ 0.15\ 0.09\ 0.12\ 0.06\ 0.1\ 0.09\ 0.03)\\ \omega C3 &= (0.08\ 0.06\ 0.13\ 0.11\ 0.16\ 0.12\ 0.14\ 0.07\ 0.06\ 0.07)\\ \omega C4 &= (0.08\ 0.07\ 0.15\ 0.06\ 0.14\ 0.17\ 0.12\ 0.09\ 0.04\ 0.08)\end{aligned} \tag{15}$$

Based on the weight vector of the four kinds of employee fuzzy judgment matrix, the weight coefficients of four kinds of employees are added to obtain the group weight vector as

$$\begin{gathered}\omega C1 = 0.3 \times 0.17 + 0.3 \times 0.1 + 0.2 \times 0.08 + 0.2 \times 0.08 = 0.113\\ \omega C2 = 0.3 \times 0.11 + 0.3 \times 0.11 + 0.2 \times 0.06 + 0.2 \times 0.07 = 0.092\\ \omega C3 = 0.3 \times 0.05 + 0.3 \times 0.15 + 0.2 \times 0.13 + 0.2 \times 0.15 = 0.116\\ \omega C4 = 0.3 \times 0.11 + 0.3 \times 0.15 + 0.2 \times 0.11 + 0.2 \times 0.06 = 0.112\\ \omega C5 = 0.3 \times 0.14 + 0.3 \times 0.09 + 0.2 \times 0.16 + 0.2 \times 0.14 = 0.129\\ \omega C6 = 0.3 \times 0.07 + 0.3 \times 0.12 + 0.2 \times 0.12 + 0.2 \times 0.17 = 0.115\\ \omega C7 = 0.3 \times 0.1 + 0.3 \times 0.06 + 0.2 \times 0.14 + 0.2 \times 0.12 = 0.1\\ \omega C8 = 0.3 \times 0.14 + 0.3 \times 0.1 + 0.2 \times 0.07 + 0.2 \times 0.09 = 0.104\\ \omega C9 = 0.3 \times 0.02 + 0.3 \times 0.09 + 0.2 \times 0.06 + 0.2 \times 0.04 = 0.044\\ \omega C10 = 0.3 \times 0.07 + 0.3 \times 0.03 + 0.2 \times 0.07 + 0.2 \times 0.08 = 0.075\end{gathered} \tag{16}$$

Therefore, the weight vector of the criterion layer B1 to the index layer is given as

$$\omega C1 = (0.113\ 0.092\ 0.116\ 0.112\ 0.129\ 0.115\ 0.1\ 0.104\ 0.044\ 0.075) \tag{17}$$

Similarly, the weight vectors of the criterion layers B2, B3, B4 to the index layer C can be summarized, as given below.

The weight vector of the criterion layer B2 to the index layer is given as

$$\omega C2 = (0.078\ 0.072\ 0.127\ 0.12\ 0.095\ 0.135\ 0.102\ 0.094\ 0.072\ 0.105) \tag{18}$$

The weight vector of criterion layer B3 to the index layer is given as

$$\omega C3 = (0.79\ 0.072\ 0.125\ 0.141\ 0.116\ 0.112\ 0.097\ 0.08\ 0.079\ 0.099) \tag{19}$$

The weight vector of criterion layer B4 to the index layer is given as

$$\omega C4 = (0.085\ 0.089\ 0.129\ 0.125\ 0.107\ 0.111\ 0.092\ 0.116\ 0.079\ 0.067) \tag{20}$$

The weight vector ωC of the target layer can be obtained by calculating the criterion layer weight vector for the target layer and the index layer. Taking C1 as the index, the weight vector of the operating capacity is calculated as

$$0.125 \times 0.133 + 0.34 \times 0.078 + 0.365 \times 0.079 + 0.17 \times 0.085 = 0.08393 \tag{21}$$

Similarly, we can derive the weight vector of 10 risk factors in the index layer as

$$\omega C = (0.0839\ 0.0774\ 0.1252\ 0.1275\ 0.109\ 0.120\ 0.0982\ 0.0939\ 0.0723\ 0.0926) \tag{22}$$

According to the degree of importance, 10 risk factors were ranked, as follows profitability (0.1275), operating capacity (0.1252), monetary fund (0.120), solvency (0.109), accounts receivable (0.0982), inventory (0.0939), past performance (0.0926), macro-enterprise environment (0.0839), enterprise development (0.0774), and enterprise credit rating (0.0723).

Based on the importance ranking, the index C layer of the ranking of the indicators and the importance of evaluating the standard level is basically the same. The indicators of business performance and asset status are at the forefront of the core corporate credit risk and are the two factors affecting core enterprise credit risk the most. Therefore, by means of a fuzzy analytic hierarchy process, a quantitative risk assessment can be performed. This approach can be very helpful in conducting key analysis observations for financial institutions to provide supply chain financing for purposes of determining the key financial indicators.

6. Concluding Remarks

The primary purpose of the paper was to analyze core enterprise credit risks in supply chain finance, by means of a 'fuzzy analytical hierarchy process' (FAHP), and to construct a supply chain financial credit risk evaluation system. This paper extended earlier work discussing the fuzzy judgment matrix, developing a fuzzy Judgment matrix consistency check, weight vector of index layer C, weight vector of index layer C to criterion layer B, and composite weight vectors. The paper also provides a detailed empirical example that highlights the novelty of the model construction and solution.

Supply chain finance is 'good medicine' to solve the financing problem of small and medium-sized enterprises, which can effectively alleviate the capital constraints of SMEs and achieve benefits for many participants in the supply chain. Therefore, core enterprises should improve their economic strength by adjusting their business strategies and innovation to enhance enterprise competitiveness, improving their asset quality and credit records to enhance their industry status and core competitiveness.

Core enterprises should also carefully select SMEs in the supply chain; choosing those with good credit status, higher industry position, and strong profitability, to ensure the overall security and stability of the supply chain, reduce credit risks, and enhance the overall competitiveness.

There are several suggestions regarding balancing the development of supply chain finance, building and dynamic improvements of the supply chain financial risk evaluation and control system, and establishing electronic databases by commercial banks. At present, supply chain finance is mainly used in automobile, steel, and other industries, which have large industry limitations.

As important participants in the supply chain, core enterprises strengthen the strategic cooperative relationship of the supply chain members, so that supply chain financing can be extended to other industries to solve the financing constraints of SMEs. The core enterprises can also use their own advantages to expand supply chain financing to other industries to maximize the profits among different industry groups. In this way, core enterprises can play an important role in supply chain finance.

Supply chain finance is involved in the exchange of capital flows, information flows, and logistics. The major participants include banks, core enterprises and SMEs. In order to maintain the interests of all parties, it is necessary to construct and perfect the risk evaluation and control system. This requires establishing a scientific concept of risk management and risk assessment based on real transactions. The main business objects involved in supply chain financing should be strictly controlled to control a variety of risks, dynamic adjustments of the arbitrary but reasonable weights, and improving the supply chain financial risk assessment system.

A unified information file should be collected based on the core enterprise, including the operating conditions, asset status, industry status, credit record, effective information to the database, collecting related data upstream and downstream of the archives around the core enterprise, developing a data information system, electronic data information, and updating the database accurately using the latest information that might be available.

Finally, through the establishment of a database on the supply chain finance, supply chain finance and modern information technology are integrated to establish the sharing of information resources, and realize the exchange of information flows, capital flows, and logistics between banks. The core enterprises and small and medium-sized enterprises will thereby function more smoothly, which not only improves the efficiency of the supply chain operation, but should also reduce a variety of risks, and improve the efficiency and effectiveness of supply chain finance.

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Appendix A. Questionnaire

The research in this paper is based on the data of the questionnaire and the case enterprise, which are objective. The data of the questionnaire have certain subjective components.

The questionnaires were based on random sampling and they did not have any economic interest in the study. In terms of economic characteristics, the sample is divided into four levels, namely management personnel, senior engineers, middle-level employees, and general employees. They have a certain degree of representation which guarantees the objectivity and reliability of the research.

The latter is aligned with the mean, so this contingency does not affect the results of the study as the focus of the study is the mean.

The questionnaire is conducted using sampling methods, and there is no conflict of interest as the employees did not have any economic interest in this study.

The paper uses a simple averaging method to take values, which should not have a significant impact on the results of the study. The data obtained from the entire questionnaire are processed in advance during the writing process. Given space limitations, the data aggregation and processing are not presented in detail.

Business friends:

First of all, thank you for completing this questionnaire. We are conducting an academic study to study the financial credit risk of supply chain. We guarantee that all survey data are for academic research only, and will not involve the trade secrets of the unit. The information obtained will not be used for any commercial purpose. We hope you will take the time to provide us with the following information. The investigation is not registered, and answers are neither right nor wrong. If there is a problem that does not fully express your opinion, please choose the answer that is closest to your opinion. Thank you for your help!

Basic Information

1. Your gender is ( ).
   A. Male B. Female
2. Your age is ( ).
   A. 20–30 years old B. 31–40 years old C. 41–50 years old D. 51–60 years old
3. Your working life in this unit is ( ).
   A. 5 years or less B. 5–10 years C. 10–20 years D. 20 years or more
4. Your position in this unit is ( ).
   A. General employees B. Middle-level employees C. Senior engineers D. Managers
5. Your department in the unit is ( ).
   A. Purchasing department B. Production department C. Sales department
   D. Finance department E. Personnel Department F. Logistics Department G. Others
6. The industry of the unit is ( ).
   A. Steel industry B. Textile industry
   C. Home appliance manufacturing D. Medical machinery industry
7. Your academic qualifications ( ).
   A. High School B. Undergraduate C. Master/Dr. D. Specialist

Credit Risk Survey

The following is a description of the financial risk indicators for the supply chain.

Please make your choices for each of the influencing factors according to your company's situation and your personal experience.

The larger is the number, the higher is the risk. For example, the choice of 1, which indicates that the risk level is very low: the choice of 2, indicating a low degree of risk; the choice of 3, indicating a moderate degree of risk; the choice of 4, indicating a high degree of risk: the choice of 5, indicating a high degree of risk. Please mark '$\surd$' on the corresponding number.

1. Criteria Layer Risk

Risk factor	Risk level				
	1	2	3	4	5
Industry status					
Operation					
Asset state					
Credit history					

2. Risks of Each Indicator Layer Under the Criteria Layer

Risk factor	Risk level				
	1	2	3	4	5
Macro environment					
Enterprise development					
Operation ability					
Profitability					
Solvency					
Monetary fund					
Accounts receivable					
Inventory					
Enterprise credit rating					
Past performance					

Appendix B. Calculation of the Fuzzy Judgment Matrices

$$C_{11} = \begin{bmatrix} 0.5 & 0.4 & 0.3 & 0.5 & 0.7 & 0.3 & 0.5 & 0.2 & 0.4 & 0.5 \\ 0.6 & 0.5 & 0.6 & 0.4 & 0.6 & 0.3 & 0.3 & 0.7 & 0.5 & 0.4 \\ 0.7 & 0.4 & 0.5 & 0.6 & 0.3 & 0.5 & 0.6 & 0.8 & 0.5 & 0.6 \\ 0.5 & 0.6 & 0.4 & 0.5 & 0.7 & 0.8 & 0.2 & 0.4 & 0.3 & 0.5 \\ 0.3 & 0.4 & 0.7 & 0.3 & 0.5 & 0.5 & 0.2 & 0.9 & 0.5 & 0.3 \\ 0.7 & 0.7 & 0.5 & 0.2 & 0.5 & 0.5 & 0.6 & 0.8 & 0.3 & 0.5 \\ 0.5 & 0.7 & 0.4 & 0.8 & 0.8 & 0.4 & 0.5 & 0.3 & 0.2 & 0.4 \\ 0.8 & 0.3 & 0.2 & 0.6 & 0.1 & 0.2 & 0.7 & 0.5 & 0.7 & 0.5 \\ 0.6 & 0.5 & 0.5 & 0.7 & 0.5 & 0.7 & 0.8 & 0.3 & 0.5 & 0.5 \\ 0.5 & 0.6 & 0.4 & 0.5 & 0.7 & 0.5 & 0.6 & 0.5 & 0.5 & 0.5 \end{bmatrix} \tag{23}$$

$$C_{12} = \begin{bmatrix} 0.5 & 0.4 & 0.7 & 0.6 & 0.5 & 0.3 & 0.4 & 0.5 & 0.7 & 0.4 \\ 0.6 & 0.5 & 0.9 & 0.5 & 0.2 & 0.5 & 0.3 & 0.4 & 0.5 & 0.5 \\ 0.3 & 0.1 & 0.5 & 0.5 & 0.4 & 0.7 & 0.6 & 0.4 & 0.5 & 0.5 \\ 0.4 & 0.5 & 0.5 & 0.5 & 0.5 & 0.6 & 0.5 & 0.3 & 0.3 & 0.4 \\ 0.5 & 0.8 & 0.6 & 0.5 & 0.5 & 0.4 & 0.5 & 0.4 & 0.6 & 0.3 \\ 0.7 & 0.5 & 0.3 & 0.4 & 0.6 & 0.5 & 0.2 & 0.5 & 0.6 & 0.5 \\ 0.6 & 0.7 & 0.4 & 0.5 & 0.5 & 0.8 & 0.5 & 0.4 & 0.6 & 0.4 \\ 0.5 & 0.6 & 0.6 & 0.7 & 0.6 & 0.5 & 0.6 & 0.5 & 0.1 & 0.3 \\ 0.3 & 0.5 & 0.5 & 0.7 & 0.4 & 0.4 & 0.4 & 0.9 & 0.5 & 0.5 \\ 0.6 & 0.5 & 0.5 & 0.6 & 0.7 & 0.5 & 0.6 & 0.7 & 0.5 & 0.5 \end{bmatrix} \tag{24}$$

$$C_{13} = \begin{bmatrix} 0.5 & 0.3 & 0.4 & 0.5 & 0.5 & 0.7 & 0.6 & 0.4 & 0.8 & 0.5 \\ 0.7 & 0.5 & 0.6 & 0.9 & 0.4 & 0.7 & 0.5 & 0.3 & 0.3 & 0.4 \\ 0.6 & 0.4 & 0.5 & 0.2 & 0.5 & 0.3 & 0.6 & 0.6 & 0.5 & 0.3 \\ 0.5 & 0.1 & 0.8 & 0.5 & 0.6 & 0.8 & 0.7 & 0.5 & 0.4 & 0.5 \\ 0.5 & 0.6 & 0.5 & 0.4 & 0.5 & 0.6 & 0.7 & 0.2 & 0.2 & 0.4 \\ 0.3 & 0.3 & 0.7 & 0.2 & 0.4 & 0.5 & 0.3 & 0.5 & 0.6 & 0.5 \\ 0.4 & 0.5 & 0.4 & 0.3 & 0.3 & 0.7 & 0.5 & 0.6 & 0.5 & 0.6 \\ 0.6 & 0.7 & 0.4 & 0.5 & 0.8 & 0.5 & 0.4 & 0.5 & 0.3 & 0.4 \\ 0.5 & 0.7 & 0.5 & 0.6 & 0.8 & 0.4 & 0.5 & 0.7 & 0.5 & 0.7 \\ 0.2 & 0.6 & 0.7 & 0.5 & 0.6 & 0.5 & 0.4 & 0.6 & 0.3 & 0.5 \end{bmatrix} \quad (25)$$

$$C_{14} = \begin{bmatrix} 0.5 & 0.3 & 0.4 & 0.6 & 0.5 & 0.5 & 0.7 & 0.4 & 0.6 & 0.7 \\ 0.7 & 0.5 & 0.5 & 0.3 & 0.6 & 0.9 & 0.5 & 0.3 & 0.5 & 0.6 \\ 0.6 & 0.5 & 0.5 & 0.6 & 0.5 & 0.6 & 0.2 & 0.4 & 0.3 & 0.5 \\ 0.4 & 0.7 & 0.4 & 0.5 & 0.4 & 0.3 & 0.7 & 0.6 & 0.5 & 0.4 \\ 0.5 & 0.4 & 0.5 & 0.6 & 0.5 & 0.4 & 0.4 & 0.5 & 0.4 & 0.2 \\ 0.5 & 0.1 & 0.4 & 0.7 & 0.6 & 0.5 & 0.7 & 0.4 & 0.5 & 0.4 \\ 0.3 & 0.5 & 0.8 & 0.3 & 0.6 & 0.3 & 0.5 & 0.2 & 0.6 & 0.5 \\ 0.6 & 0.7 & 0.6 & 0.4 & 0.5 & 0.6 & 0.8 & 0.5 & 0.4 & 0.2 \\ 0.4 & 0.5 & 0.7 & 0.5 & 0.6 & 0.5 & 0.4 & 0.6 & 0.5 & 0.7 \\ 0.3 & 0.4 & 0.5 & 0.6 & 0.8 & 0.6 & 0.5 & 0.8 & 0.3 & 0.5 \end{bmatrix} \quad (26)$$

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